Artificial Intelligence, Firm Growth, and Product Innovation[*]

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Abstract

We study the use and economic impact of AI technologies. We propose a new measure of firm-level AI investments using worker resume data. Our measure reveals a stark increase in AI investments across sectors. AI-investing firms experience increased growth in sales, employment, and market valuations. This growth comes primarily through increased product innovation. Our results are robust to instrumenting AI investments using firms' exposure to universities' supply of AI graduates. AI-powered growth concentrates among ex-ante larger firms, leading to higher industry concentration. Our results highlight that new technologies like AI can contribute to growth and superstar firms through product innovation.

Keywords: artificial intelligence, intangible capital, technological change, technology adoption, economic growth, product innovation, productivity, human capital, superstar firms, industry concentration

JEL codes: D22, E22, J23, J24, L11, O33

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Technological change is a key driver of investment opportunities and economic growth (Romer, 1990; Aghion and Howitt, 1992; Kogan et al., 2017). The past decade has seen a new technological shift: substantial developments in artificial intelligence (AI) technologies and their wide-spread commercial application (Furman and Seamans 2019). As a prediction technology, AI allows firms to learn better and faster from vast quantities of data, with the potential to significantly improving business decision-making. As such, AI can be a general purpose technology that generates growth through increased productivity and product innovation across a wide range of sectors (Aghion et al., 2017; Agrawal et al., 2019).[1] Yet it remains an open question whether AI can transform economies and spur economic growth, as lackluster aggregate productivity growth over the past decade has led to concerns that the benefits of AI may be over-hyped or take a much longer time to materialize (Mihet and Philippon, 2019; Brynjolfsson et al., 2019). To date, the lack of comprehensive data on firm-level AI adoption has posed the key challenge to understanding the adoption patterns and the economic impact of AI technologies (Seamans and Raj, 2018).

In this paper, we propose a new measure of investments in AI technologies based on firms' AI-skilled human capital. The heavy reliance of AI on human expertise makes the human-capital-based approach particularly well-suited in this setting. We take advantage of a unique combination of datasets that capture both the *stock* of and the *demand* for AI-skilled employees among U.S. firms: resume data from Cognism Inc, which offer job histories for 535 million individuals globally, and job postings data from Burning Glass, which capture 180 million job vacancies. Our new AI measure allows us to analyze the patterns of AI adoption and examine its potential benefits for the adopting firms and industries. Our main takeaway is that firms that invest more in AI experience higher growth through increased product innovation, which can be seen in increased trademarks, product patents, and updates to firms' product portfolios. Our results suggest that, so far, the first-order effect of AI has been in empowering growth through product innovation, consistent with AI reducing the costs of product development.

Our work offers several innovations over the existing literature. First, we introduce a novel measure of firm-level investments in AI technologies. Our detailed data and measure allow us to study the impact of AI technologies on firms, whereas other studies focus on the impact of AI on labor (Acemoglu et al., 2020b) and tend to look at the occupation or aggregate level (e.g., Felten et al., 2019). We provide novel evidence that AI investments contribute to firm growth and explore the mechanisms by which this growth can accrue. Second, we are able to measure AI adoption for a broad sample of AI-*using* firms across a wide range of industries, which complements recent work that focuses on AI-*inventing* firms (Alderucci et al., 2020). Our broad industry coverage allows us to examine the implications of AI investments for aggregate trends such as industry

[1] In a 2018 Deloitte survey of executives at companies investing in AI, 70% anticipate that AI will fundamentally transform their companies and industries within the next five years.

growth and concentration. Third, in the absence of administrative U.S. firm-worker matched data with individual workers' occupations, our Cognism resume data provide unique coverage of U.S. jobs with detailed job descriptions while representing more than 64% of full-time U.S. employment as of 2018.[2] This enables us to compare AI labor demand identified from job postings with the stock of AI workers identified from resumes. Finally, our rich data on firms' human capital allow us to measure and control for confounding factors, such as the use of non-AI information technologies, and capture the use of external AI solutions and software (e.g., IPSoft Amelia).

Even with our detailed data, identifying firms' AI investments is challenging due to the multi-faceted nature of AI applications.[3] We circumvent this challenge by proposing a new data-driven approach to identify AI-related jobs, which does not depend on pre-specified lists of keywords. Instead, our algorithm learns the AI-relatedness of each job empirically from the detailed skills of the job postings. First, we measure the AI-relatedness of each skill in the job postings data, based on that skill's co-occurrence with the core AI skills—machine learning, computer vision, and natural language processing. Second, we obtain a measure of AI-relatedness of each job posting by averaging the AI-relatedness of all skills required by the job posting. Finally, we leverage the most AI-related skills identified from the job postings data to classify AI workers in the less structured resume data. For each employee, we consider whether skills with the highest AI-relatedness (e.g., "deep learning") appear either in the job title, in the job description, or in any publications, patents, or awards received during that job. This gives us a classification of each employee of each firm at each point in time. We aggregate both resume data and the job postings data to the firm level and match to public firms in the Compustat data. Encouragingly, the two measures of AI investments, although based on two independent datasets, are highly correlated and yield consistent results.

We confirm that our human-capital-based measures of AI investments display intuitive properties. First, we confirm that our AI measure does not pick up general data-related skills, only those that are specifically associated with AI implementation. Second, we manually inspect large samples of AI-classified jobs and confirm that our classification picks up highly AI-skilled positions. Third, given that we do not use job titles to identify AI-related skills, we validate our measure by confirming that the job postings with the highest AI-relatedness measures skew heavily towards highly AI-specific job titles. Fourth, we provide detailed case studies of specific applications of AI within several firms. Fifth, we confirm that AI-investing firms also increase research

[2]For comparison, while the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program provides firm-worker matched data and worker wages, it does not include any information on workers' occupations or their jobs (Abowd et al., 2009; Haltiwanger et al., 2014). Moreover, a typical project using the LEHD data does not have access to all states due to administrative reasons: for example, Babina (2020) has access to about 40% of employment and Babina and Howell (2018)—60%.

[3]Within a single firm, e.g., Caterpillar Inc., AI can have use cases ranging from improving machinery via computer vision to offering a new product line of Internet of Things style analytics to machine operators.

and development (R&D) expenditures, consistent with increased experimentation with applying the new AI technologies. Finally, we enrich our baseline measure by incorporating the use of external AI solutions and software, confirming that this augmented measure yields very similar results.

We begin our analysis by describing key patterns in AI investments. In both employee resume and job postings datasets, the fraction of AI jobs has increased dramatically over time, growing more than seven-fold from 2010 to 2018. The share of AI jobs is highest in the technology sector, but the rate of increase in AI investments over time is similar across sectors. At the firm level, growth in AI investments is more pronounced among ex ante larger firms and firms with higher cash holdings and R&D intensity. Looking at the local labor market conditions, we observe that higher-wage and more educated areas experience faster growth in AI-skilled hiring.

We next address the fundamental question of whether AI investments are associated with higher firm growth. As is standard in settings with slow-moving processes like technological change (e.g., Acemoglu and Restrepo, 2020), our primary specification is a long-differences regression of changes in firm outcomes from 2010 to 2018 on changes in firm-level AI-skilled human capital, measured by the share of AI workers. This strategy is especially well-suited for our setting, where AI investments accumulate gradually over time and generate effects that may not be immediate. We include a rich set of controls: industry fixed effects and firm-, industry-, and commuting-zone-level characteristics in 2010. We document a strong and consistent pattern of higher growth among firms that invest more in AI: a one-standard-deviation increase in the resume-based measure of AI investments over the 8-year period corresponds to a 20.3% increase in sales, a 21.7% increase in employment, and a 22.4% increase in market valuation. The results are ubiquitous across major industry sectors (e.g., manufacturing, finance, and retail), supporting the idea that AI is a general purpose technology.

While the long-differences specification controls for time-invariant firm characteristics, we perform several tests to address concerns about omitted variables or reverse causality and buttress a causal interpretation of our results. First, we exploit firm-level panel data to examine firm growth dynamically in each year around AI investments using a standard distributed lead-lag model (Aghion et al., 2020). We find no pre-trends in firm growth prior to AI investments, confirming that AI-investing firms are not on differential growth trends, and a positive effect after a lag of two to three years, suggesting that the effects of AI are not immediate. Second, the results are robust to the inclusion of controls for past firm and industry growth and future growth opportunities proxied by Tobin's q. Third, we confirm that our results reflect specifically investments in AI, rather than other technologies: the effects of AI investments remain unchanged when controlling for contemporaneous firm-level investments in robotics, non-AI information technologies,

and non-AI data analytics.

To further address concerns regarding unobserved shocks driving both firm growth and AI investments, we use a novel instrumental variables strategy: we instrument for firm-level AI investments using variation in firms' ex-ante exposure to the subsequent supply of AI talent from universities that are historically strong in AI research. The core idea is that the scarcity of AI-trained labor is one of the most important constraints to firms' AI adoption (e.g., CorrelationOne, 2019), and universities that are historically strong in AI research have been able to train more AI-skilled graduates in recent years, enabling firms that historically hired from those universities to more readily recruit AI talent. To construct the instrument, we compile two new datasets on (i) the ex-ante strength of AI research in each university and (ii) firm-university hiring networks prior to 2010 to measure firms' exposure to AI-strong universities. Consistent with commercial interest in AI becoming widespread only since 2012, we show that firms' connections to AI-strong universities in 2010 were not driven by the need to hire AI-skilled workers and do not correlate with firm growth before 2010. The instrument has a strong first stage, and we show that the instrumented firm-level growth in AI investments robustly predicts firm growth between 2010 and 2018. We verify that these results are not driven by other characteristics of AI-strong universities such as strength in general computer science or overall university ranking.

We next explore the mechanisms through which AI generates firm growth. We provide a theoretical framework in which AI can lead to firm growth through two non-mutually-exclusive channels: (i) product innovation and (ii) process innovation and reduction in operating costs. According to the first channel, AI can reduce the costs of product innovation, which improves the quality of existing products and allows firms to create new products (Klette and Kortum, 2004a; Hottman et al., 2016). Theoretically, AI can potentially reduce the costs of product innovation in several ways. First, since product development involves lengthy experimentation with uncertain benefits (Braguinsky et al., 2020), the ability of AI algorithms to quickly learn from large datasets can reduce the uncertainty of experimentation in product development and make the process of learning about promising projects more efficient. For example, at Moderna, AI algorithms have been leveraged in the development of the first COVID-19 vaccine in just 65 days, a process that would previously take years. Second, AI algorithms themselves can constitute improved products (e.g., AI-powered trading platforms). Third, AI can contribute to increased product scope by improving firms' ability to learn about customer preferences and tailor product offerings to customer tastes (Mihet and Philippon, 2019). Empirically, we find that firms with larger AI investments see increased product innovation, reflected in more product patents (i.e., patents focusing on product innovation, see Ganglmair et al., 2021), trademarks (Hsu et al., 2021), and updates to product portfolios (Hoberg and Phillips, 2016).

The second channel through which AI can stimulate growth is by lowering operating costs and improving productivity for existing products, for example, by replacing human labor for some tasks (Agrawal et al., 2019) or by increasing operational efficiency through better forecasting and more efficient processes (Basu et al., 2001; Farboodi and Veldkamp, 2021). Empirically, we do not find support for this second channel. AI investments are not associated with changes in sales per worker, total factor productivity, or process patents (i.e., patents focusing on process innovation).

Our final set of results speak to potential aggregate effects of AI on industry dynamics. First, we note that the benefits from AI investments are unevenly distributed across firms, consistent with the hypothesis that AI can increase inequality by favoring large firms with more data, which is a crucial input to AI implementation (Mihet and Philippon, 2019; Farboodi et al., 2019). We estimate the effect of AI investments within groups of firms by initial size and find that the positive relationship between AI investments and firm growth is much stronger among ex-ante larger firms. We then test whether firm-level growth translates into industry-level growth. It is possible that the positive effects on AI-investing firms are offset or even dominated by negative spillovers to competitors within the industry, and Basu et al. (2006) show that the use of technology can be contractionary at the aggregate level if input use declines. Nevertheless, we find that industries that invest more in AI experience an overall increase in sales and employment within the sample of Compustat firms. Finally, AI investments are associated with increased industry concentration, consistent with our finding that AI favors ex-ante larger firms with more data. This suggests that AI investments can affect industry dynamics by reinforcing winner-take-most dynamics.

Overall, we document that AI is strongly associated with higher firm growth, and this growth comes mainly from firms' use of AI technologies for product innovation. This mechanism reflects the nature of AI as a prediction technology. Predictions are essential for firms' decision-making across all aspects of operations and particularly in product development, which requires experimentation and learning about promising projects and customer preferences (Braguinsky et al., 2020). The ability to perform better predictions with AI can create new business opportunities. In this context, our paper offers micro-level evidence and helps to unpack the black box of where "new projects" and investment opportunities come from: new technologies like AI, which allow firms to learn better and faster, can expand the investment opportunity frontier by decreasing firms' product development costs.

Related Literature

Our paper provides one of the first pieces of systematic evidence for the impact of artificial intelligence on firms and the economy. Recent work makes progress in examining the impact of AI technologies on firm activities in various settings: robo-advising (D'Acunto et al., 2019),

fintech innovation (Chen et al., 2019), loan underwriting (Jansen et al., 2020; Fuster et al., 2020), financial analysts (Grennan and Michaely, 2019; Abis and Veldkamp, 2020; Cao et al., 2021), and entrepreneurship (Gofman and Jin, 2020). Acemoglu et al. (2021) use Burning Glass job postings data to study the effect of exposure to AI technologies based on firms' occupation structure on labor demand. Our comprehensive data on firm employees and data-driven approach allow us to measure actual AI investments across a wide range of industries and shed light on how AI stimulates economic growth as a general purpose technology (Aghion et al., 2017; Mihet and Philippon, 2019). [4]Our empirical evidence supports this view and offers an additional insight: the mechanism through which AI fuels growth is by empowering product innovation, which has been considered a key mechanism for firm growth (e.g., Hottman et al., 2016; Argente et al., 2021). These findings help explain Rock (2019), who shows that the launch of Google's TensorFlow expedited the gain in market valuations associated with firms' exposure to AI, with null effects on productivity.

Methodologically, our paper offers a new approach to measure firms' intangible capital based on human capital, with a specific application to capturing investments in AI. Despite ongoing efforts to measure intangibles in the U.S. at the national level (Corrado et al., 2016), most firm-level measures of intangible capital use cost items such as R&D and SG&A (e.g., Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017; Crouzet and Eberly, 2019; Eisfeldt et al., 2020). Our methodology offers a new measure of intangibles related to technology use that is consistent across firms and sectors and can be applied to measure various forms of intangible assets, especially those based on human expertise. For example, while we focus on AI investments, we are also able to measure firm investments in robotics, non-AI information technology, and non-AI data analytics. More broadly, our method contributes to the growing literature that uses textual analysis to measure intangibles such as human capital and innovation. For example, Hoberg and Phillips (2016) analyze text of 10-K filings to create measures of firms' product portfolios, Kogan et al. (2019) construct occupation-specific indicators of technological change using patent text, Fedyk and Hodson (2019) use textual analysis to measure firms' focus on technical skills, Argente et al. (2020) map patent text to products, and Babina et al. (2020) use patent text to measure technological entrepreneurship.

Finally, we contribute to the recent literature on industry concentration and superstar firms (e.g., Gutiérrez and Philippon, 2017; Covarrubias et al., 2019; Autor et al., 2020). Our findings suggest that technologies like AI have scale advantages and may be an important driver of the superstar firms phenomenon. This supports the hypothesis that intangible assets propel growth

[4]Our firm-level measures of AI investments based on human capital are complementary to recent work that measures technology adoption using survey data (e.g., Brynjolfsson and McElheran, 2016; Acemoglu et al., 2022). To foster further research on the economic impact of AI, all code to generate our AI investment measures and our firm-level AI data will be publicly available on the authors' websites.

of the largest firms and contribute to increased industry concentration (e.g., Crouzet and Eberly, 2019). In particular, AI appears to reduce the costs of product development that are especially high for large firms (Akcigit and Kerr, 2018), allowing these firms to scale more easily. Finally, our evidence also consistent with the lack of productivity growth among superstar firms documented in Gutiérrez and Philippon (2019).

1 Artificial Intelligence: Background and Mechanisms

According to the Organisation for Economic Co-operation and Development (2019), an AI system is defined as a *"Machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions."* We provide a brief overview of the current commercial use and key features of AI, followed by a discussion on economic mechanisms through which AI investments might lead to higher firm growth across a broad range of industries.

1.1 Artificial Intelligence: A Brief Overview

Commercial applications and investments in AI have increased exponentially over the past decade. While there are no systematic data on AI investments by firms, recent estimates hover around $140 billion globally per year.[5] There has also been an expansion of AI investments across industry sectors. While the tech sector was an early adopter of AI, surveys of executives indicate widespread adoption of AI technologies by firms in all industries (see here for a survey by McKinsey).

Academic research in AI has flourished for decades since John McCarthy coined the term in 1955 (McCarthy et al., 1955).[6] The recent explosion of commercial interest in AI in the private sector is driven by supply-side factors: rapid accumulation of data, decreasing costs of computation, and advances in methodologies, including deep learning (Hodson, 2016). In terms of commercial applications, three key areas of AI have captured the bulk of private sector investments: machine learning, natural language processing, and computer vision.[7] These core techniques are united by their ability to perform high-skilled, non-routine tasks, such as prediction, detection, and classification (Agrawal et al., 2019). Their main distinction from traditional methods of data analysis consists of these techniques' ability to learn from vast quantities of high-dimensional data (including text, speech, and image data; Hauptmann et al., 2015) and significantly improve the accuracy of predictions. For example, the ImageNet challenge in 2012 led to an almost halving of image

[5]See the PitchBook AI & ML Emerging Tech Report 2021 here.

[6]A brief history of AI research can be found here.

[7]See here for a survey by Deloitte in 2018. While our focus is on AI technologies rather than automation technologies like ATMs and industrial robots, our measure does incorporate relevant recent robotics technologies (e.g., autonomous vehicles, vision-guided robots) that are highly related to computer vision and machine learning technologies.

recognition error rates (relative to traditional methods), which launched large corporate interest in the computer vision space.[8]

AI has several key economic properties. First, AI is a prediction technology, and predictions are at the heart of decision-making under uncertainty—faced by firms in all aspects of their operations. As a result, the ability to perform better predictions with AI can create new business opportunities. Second, economists have argued that AI is a general purpose technology (GPT) and can be leveraged across different business segments and sectors to solve a wide range of business problems. Examples of GPT include the steam engine, electricity, and the Internet. Third, investments in AI center around human expertise, with complementary investments in computing technology and data infrastructure. This differs from technologies that require mainly capital investments, such as industrial robots (Benmelech and Zator, 2022). As such, AI is an intangible asset, reflecting the broader shift towards intangible capital (Mihet and Philippon, 2019). The fourth key feature of AI technologies is that they are information goods with non-rival uses: new algorithms are usually published openly and can be used simultaneously by many firms. However, the extent to which AI can benefit firms depends to a large extent on who owns big data—the key input to AI technologies (Fedyk, 2016; Jones and Tonetti, 2020).

1.2 Artificial Intelligence and Firm Growth: Mechanisms

It is an open question whether and how investments in AI technologies benefit firms. On the one hand, as a potential general purpose technology, AI might spur economic growth. On the other hand, current attention to AI may be over-hyped (Mihet and Philippon, 2019), or AI may still be too early in the adoption cycle to have a meaningful impact on firm growth (Brynjolfsson et al., 2020).

In Online Appendix A1, we present a model with multi-product firms, and outline how AI can lead to firm growth either through process innovation or product innovation. Below, we discuss intuitions and predictions for these two non-mutually-exclusive channels.

AI as a Driver of Product Innovation. AI can lead to firm growth by reducing the costs of product innovation. Product innovation and the expansion of product varieties is an important mechanism for firm growth (Klette and Kortum, 2004b; Hottman et al., 2016). Product innovation can increase the product appeal and demand for existing products or enable firms to expand their product offerings. Braguinsky et al. (2020) point out that product variety and product appeal are endogenously determined through experimentation by firms, and AI can potentially facilitate the accumulation of knowledge through experimentation and reduced costs of product innovation (Bustamante et al., 2020). According to surveys of executives, enhancement of existing products

[8] See ImageNet Large Scale Visual Recognition Challenge 2012 (ILSVRC2012).

and services and the creation of new ones is the top use of AI to date (see here for a survey by Deloitte).

As a prediction technology, AI can potentially affect product innovation in several ways. First, the ability of AI algorithms to quickly analyze large datasets and learn about the underlying relationships from data can potentially reduce the uncertainty of experimentation and make the learning process more efficient, which leads to more experimentation and creation of new products (Cockburn et al., 2018). In practice, recent years show a number of ways in which AI has enabled or sped up the product innovation process. For example, AI can shorten the drug development life cycle. At Moderna, AI algorithms have contributed to the development and the production of the first dose of the COVID-19 vaccine in just 65 days, a process that would previously take years.[9]

Second, AI algorithms can help innovate on the quality of existing products and services by building AI models directly into products. For example, in Online Appendix A2, we offer detailed case studies of the applications of AI, which show examples of AI empowering the introduction of the AI-driven trading platform DeepX at JPMorgan (which allows for faster and cheaper execution of trades) and "smart" machinery at Caterpillar (which improves machine safety and flexibility).

Third, AI can also improve product appeal by helping firms learn about customer preferences more efficiently and therefore better tailor product and service offerings to customers' tastes and needs. When firms launch new products or expand their product variety, they face uncertainty regarding what customers want and how customer preferences might change. Using AI to analyze customer data can potentially enable firms to overcome this hurdle, providing "the right product on a hyper-individualized basis" (Hodson, 2016) and overcoming frictions in firms' demand accumulation processes (Foster et al., 2016; Argente et al., 2021). For example, data on individual behaviors, such as web browsing and location history and other digital footprints, can enable better approximations of parameters entering individual demand functions than pure demographic information, leading to more heterogeneity in products tailored to customers with different tastes (Mihet and Philippon, 2019).

AI as a Driver of Process Innovation and Lower Operating Costs. AI can also lead to firm growth by reducing the costs of process innovation. Process innovation improves firms' productivity in producing their existing products, and many prior technological innovations have aimed at lowering operating costs and improving productivity (e.g., Basu et al. 2001; Cardona et al. 2013; Acemoglu et al. 2020a).

[9]See here and here, where Dave Johnson, Moderna's VP of Informatics, Data Science, and AI, explains how Moderna was able to develop a COVID vaccine so quickly: "We very purposely designed all this infrastructure that we think of as an AI factory, in order to rapidly deliver algorithms from concept to production, to enable our scientists to leverage the power of AI in their daily jobs. [...] That allows our scientists to design novel mRNA constructs, use AI algorithms to optimize them, and then order them from our high throughput preclinical scale production line."

In theory, AI technologies can stimulate process innovation and productivity improvements in at least two ways. First, AI can potentially replace human labor for some tasks (Agrawal et al., 2019**),** cutting per-unit labor costs. Specifically, the ability of AI to aid in the decision-making process and in solving complex cognition problems has led to concerns that AI can disrupt high-skill and high-wage occupations, in contrast to previous waves of technology adoption (Webb, 2020). Second, AI can increase operational and production efficiency through better forecasting (Mihet and Philippon, 2019). Tanaka et al. (2019) present a model of firm input choice under uncertainty and costly adjustment, where forecast errors result in under- or over-investment. AI can potentially help reduce forecast errors and optimize input decisions by firms.

The potential to use AI-based forecasting for streamlining firms' existing operations can be seen in our data. The case studies in Online Appendix A2 highlight how AI-enabled forecasting improves firm operations across a variety of industries: for example, AI workers at JPMorgan Chase model default of non-performing loans; Caterpillar leverages AI for inventory management; and UnitedHealth uses AI to support efficient medical billing.

These two mechanisms have different empirical predictions. Product innovation predicts creation of new products, improvements in product quality, and expansion of product portfolios, whereas process innovation does not affect firms' product portfolios. In terms of productivity, process innovation leads to lower operating costs and higher productivity, but the effect of product innovation on productivity is ambiguous. Studies on previous general purpose technologies mostly find positive effects on productivity (e.g., Fizsbein et al., 2020; Acemoglu et al., 2020a), and some also show a positive effect on product innovation (e.g., Bartel et al., 2007). We will empirically examine the channels through which AI affects firm growth in Section 5.

2 Data

We propose a new measure of firms' investments in AI based on their intensity of AI-skilled hiring. AI-skilled labor is a key input to AI implementation. Other inputs to AI, such as data and computing infrastructure, are complementary to AI-skilled human capital, so our human-capital-based measure allows us to capture the relative intensity of AI investments across firms.

A central challenge in the literature on the economic impact of AI is the dearth of firm-level data on AI investments. We overcome this challenge by leveraging rich datasets on firms' employee profiles and job postings simultaneously measuring firms' *stock* of AI workers and *demand* for AI workers. We detail each dataset and describe our sample construction process.

2.1 Employment Profiles from Cognism

We use employee resumes to measure the actual *stock* of AI workers at each firm. We leverage a novel dataset of approximately 535 million individual profiles provided by Cognism, an aggregator of employment profiles for lead generation and client relationship management services. Cognism obtains the resumes from a variety of sources, including publicly available online profiles, collaborations with recruiting agencies, third party resume aggregators, human resources databases of partner organizations, and direct user contributed data.[10] These data are introduced and described in detail in Fedyk and Hodson (2019). While the data slightly over-represent high-skilled employees, they cover approximately 64% of the entire U.S. workforce as of 2018 and offer a representative breakdown across industries. For each employment record listed by the individual, we see the start and end dates, the job title, the company name, and the job description. Individuals may also list their patents, awards, and publications. Cognism's AI Research department leverages techniques from machine learning and natural language processing, including named entity disambiguation and graph-based modeling methods, to further enrich the resume data by normalizing job titles and occupations, associating employees with functional divisions and teams within each firm, and identifying institutions, degrees, and majors from education records.[11]

We match employer names in the Cognism data to the company names in the Compustat data. Fedyk and Hodson (2019) provide further details on the procedure as applied to the resume data. The matching of individual resumes to firm entities is performed dynamically to account for acquisitions and divestitures. Of the 657 million US-based person-firm-year employment records between 2007 and 2018, 120 million (18%) are matched to U.S. public firms. This is consistent with approximately 26% of overall U.S. employment being accounted for by publicly listed firms (Davis et al., 2006). The sample of 120 million person-firm-years matched to U.S. public firms is comprised of 19 million distinct individual employees.

2.2 Job Postings from Burning Glass

The second dataset we use covers over 180 million job postings in the United States in 2007 and 2010–2018. The dataset is provided by Burning Glass Technologies (BG in short) and draws from a rich set of sources. BG examines more than 40,000 online job boards and company websites, aggregates the job postings data, parses them into a systematic, machine-readable form, and creates labor market analytic products. The company employs a sophisticated deduplication algorithm to avoid double counting vacancies that post on multiple job boards. BG data contain detailed

[10] The processing of all profiles is compliant with the applicable GDPR and CCPA regulations.

[11] The data snapshot is from July of 2021. Following Tambe et al. (2020), we only use the years through 2018, because the lag in workers updating their resumes could otherwise add significant noise to our measures.

information for each job posting, including job title, job location, occupation, and employer name. Importantly, the job postings are tagged with thousands of specific skills standardized from the open text in each job opening. The main advantages of the BG dataset are the breadth of its coverage and the rich detail of the individual job postings. The dataset captures the near-universe of jobs posted online and covers approximately 60–70% of all vacancies posted in the U.S., either online or offline. Hershbein and Kahn (2018) provide a detailed description of the BG data and show that their representativeness is stable over time at the occupation level. Burning Glass job postings complement our main Cognism resume dataset for two reasons. First, we take advantage of the detailed taxonomy of skills in the job postings data to empirically identify highly AI-relevant skills, as we detail in Section 3.1. Second, Burning Glass job postings data are widely accessible to the academic community; by validating them against Cognism resume data, we show that, in absence of matched employer-employee data, job postings can serve a proxy for firms' technological investments.

We focus on jobs with non-missing employer names and at least one required skill. About 65% of job postings have employer information and 93% of job postings require at least one skill.[12] We also drop job postings that are internships. We then match the employer firms in the remaining job postings to Compustat firms. This step is necessary to aggregate job postings to the firm level and merge with other firm-level variables. We perform a fuzzy matching between firm names in BG and Compustat after stripping out common endings such as "Inc" and "L.P.". For observations that do not match exactly on firm name, we manually assess the top ten potential fuzzy matches by looking at the firm name, industry, and location. Out of 112 million job postings with non-missing employer names and skills, 42 million (38%) are matched to Compustat firms. This slightly over-represents employees of publicly listed firms, which constitute just over one fourth of U.S. employment in the non-farm business sector (Davis et al., 2006).

2.3 Additional Data Sources

We merge the Cognism resume data and the Burning Glass job postings data with several additional data sources. We collect commuting-zone-level wage and education data from the Census American Community Surveys (ACS), industry-level wages and employment data from the Census Quarterly Workforce Indicators (QWI), and academic publications from the Open Academic Graph (described in detail in Appendix A). Firm-level operational variables (e.g., sales, employment, market value) come from Compustat.

[12]Job postings with missing employer names are primarily those listed on recruiting websites that mask the employers' identities.

3 Methodology and Descriptive Evidence

We use the Cognism resume data described in Section 2 to construct a human-capital-based measure of firm-level AI investments. To do this, we first leverage job postings data to learn the most AI-related skills directly from the data; we then focus on the most empirically-AI-related skills and identify them in the resume data. We aggregate the worker-level data to the firm level by calculating the share of each firm's employees who are AI-skilled.

3.1 AI Investments from Job Postings (Burning Glass)

We take advantage of the detailed information on required skills in the job postings data to propose a new data-driven methodology for identifying AI-related skills. Other work relies on pre-specified lists of key terms,[13] which is likely to suffer from both Type I (incorrectly labeling tangentially-related employees as AI-related) and Type II (missing real AI skills that did not make the initial dictionary) errors due to the arbitrariness of the list of keywords. This is especially relevant in a quickly-evolving domain such as AI, where new emerging skills can easily be missed. Our methodology circumvents these challenges by learning the AI-relatedness of each of approximately 15,000 unique skills directly from the job postings data, based on their empirical co-occurrence (within required lists of skills across job postings) with unambiguous core AI skills. We then aggregate the skill-level measure to the job level by generating a continuous measure of AI-relatedness for each job posting, from which we can classify employees into AI-skilled workers and non-AI-skilled workers.

To measure the AI-relatedness of each skill, we calculate the skill's co-occurrence with Artificial Intelligence (AI) and its three main sub-fields: machine learning (ML), natural language processing (NLP), and computer vision (CV):

$$w_s^{AI} = \frac{\text{\# of jobs requiring skill } s \text{ and (ML, NLP, CV or AI in required skills or in job title)}}{\text{\# of jobs requiring skill } s}$$

Intuitively, this measure captures how correlated each skill s is with the core AI skills. For example, the skill "Tensorflow" has a value of 0.9, which means that 90% of job postings with Tensorflow as a required skill also require one of the core AI skills or contain one of the core AI skills in the job title. Hence, a "Tensorflow" requirement in a job posting is highly indicative of that job being AI-related. On the other hand, the AI-relatedness measure of the skill "Microsoft Office" is only 0.003. We list the skills with the highest AI-relatedness measures in Online Appendix Table A1.

[13]For example, Hershbein and Kahn (2018) classify jobs as requiring cognitive abilities if any listed skills include at least one of the following terms: "research," "analy-," "decision," "solving," "math," "statistic," or "thinking." Similar bag-of-words approaches with pre-specified search terms are used to identify AI-related employees (e.g., Alekseeva et al., 2020; Acemoglu et al., 2021).

We define the job-posting-level AI-relatedness measure ω_j^{AI} for a given job posting j as the mean skill-level measure w_s^{AI} across all skills required by job posting j. We transform the continuous AI measure into a binary indicator by defining each job posting j as AI-related if the measure ω_j^{AI} is above 0.1, a threshold that captures the full range of AI-related technical jobs while minimizing false positives based on manual inspection of the data. The firm-level measure $Share_{f,t}^{AI}$ is then defined as the fraction of job postings by firm f in year t that are AI-related (i.e. $\omega_j^{AI} > 0.1$).[14] We use a discrete classification for ease of interpretability and consistency with the resume-based measure in Section 3.2, but we show in Section 4.1 that the results are robust to: (i) alternative cut-offs (e.g., 0.05 and 0.15), and (ii) using the continuous measure ω_j^{AI} aggregated to the firm level. This job-postings-based measure of AI investments provides a secondary measure to our main measure based on the stock of employees, obtained from the resume data as described in the next subsection.

Online Appendix Table A2 provides examples of AI-related and non-AI-related job postings. For each job, the continuous AI measure is the average AI-relatedness of all required skills. Our measure enables us to capture a wide range of AI-related jobs, from data scientists to speech recognition scientists to autonomous vehicle engineers. While many AI-related jobs are data scientists and similar data-analysis-related jobs, our measure differentiates data-analysis jobs specifically related to AI (job postings numbered 6–10) from data-analysis jobs that are not specific to AI and that focus on more traditional statistical methods (job postings numbered 11–15). In addition, we further ensure that our measure is not picking up general programming or statistics skills not specific to AI by showing (in Section 4.1) the robustness of our results to manually refining our measure. In particular, we screen out skills that represent general programming languages (e.g., Python) or statistics (e.g., linear regression) and only keep skills that relate specifically to AI, including AI methodology or algorithms (e.g., supervised learning) and AI software (e.g., Tensorflow). This process, curated by the AI-trained personnel at the AI for Good Foundation, categorizes the 700 skills that have an AI-relatedness measure above 0.05 and are required in at least 50 job postings into "narrow" and "broad" AI skills. This refinement mainly leaves out skills with relatively lower AI-relatedness measures and empirically has little effect on the results.[15]

[14]Throughout our empirical analyses, we focus on jobs that are matched to Compustat firms. Online Appendix Figure A1 plots the share of all job postings and the share of AI-related job postings that are matched to Compustat in each year. Although publicly listed firms constitute 38% of all job postings, they account for approximately half of all AI-related job postings. This suggests that, on average, publicly-listed firms hire more AI workers than private firms.

[15]For example, among the 50 skills with the highest AI-relatedness measures, 49 are classified as narrow AI skills (the single exception is "statsmodels," a Python package for general statistical analysis).

3.2 AI Investments from Resumes (Cognism)

For our main measure of firms' AI investments, we identify the employees in the Cognism resume data whose job positions directly involve AI. We begin with the set of 67 keywords in Online Appendix Table A1, which are skills with the highest skill-level AI-relatedness measures. We then search for these terms in every employment record of each individual in the resume data to see whether: (i) that job (role and description) directly includes any of the identified AI terms; (ii) any patents obtained during the year of interest or the two following years (to account for the time lag between the work and the patent grant) include these AI terms; (iii) any publications during the year of interest or the following year include the AI terms; and (iv) any of the identified AI terms appear in awards received during the year of interest or the following year. If any of these conditions are met, then that person at that firm in that year is classified as an AI-related employee. For example, jobs with titles such as "senior *machine learning* developer" or job descriptions such as "develop chatbots using Python with *Tensorflow* and *deep learning* models" are identified as AI jobs.

After classifying each individual in each year, we use the number of AI-related employees and the number of total employees at each firm in each year to compute the percentage of employees of that firm in that year who are classified as AI-related. Given that our empirical analyses focus on U.S.-listed firms, our firm-level measure focuses on the employees who are based in the U.S.

3.3 Summary Statistics and Validation

We examine both of our constructed measures of AI investments, confirm that they display intuitive properties, and discuss how our resume data help address potential limitations of measuring AI investments through job postings. Validating our novel measure is challenging, given the lack of existing firm-level measures of AI investments. However, we show that our measure displays a number of intuitive properties, captures specifically AI investments, and does not suffer from biases such as firms investing in AI by acquiring AI startups.

First, we document that both measures—based on resumes and job postings—display a natural rise over time, increasing more than seven-fold from 2010 to 2018. Panel (a) of Figure 1 shows a rapid increase in the fraction of employees who we classify as AI-related: this fraction starts at 0.04% in 2007 and reaches 0.29% in 2018. Panel (b) shows analogous patterns in the job postings data: the fraction of AI-skilled job postings starts out at 0.1% in 2010, rises rapidly over time (with the increase speeding up from 2014 to 2018), and peaks at 0.8% in 2018. There is substantial heterogeneity in the growth in AI-skilled labor across individual firms, which provides the variation needed to examine the relationship between AI investments and firm outcomes. For the entire sample of public firms, while a median firm sees an increase of 0% (0%) in the resume-based (job-

postings-based) measure, this increase is 0.35% (1.33%) at the 90th percentile, 0.62% (2.99%) at the 95th, and 2.22% (8.11%) at the 99th percentile.

It is helpful to put into perspective the incidence of AI-skilled workers among U.S. employees. While AI workers constitute a relatively small fraction of total employment, skyrocketing demand for AI skills and correspondingly high salaries that they command—on the order of millions of dollars for prominent AI-researchers (Gofman and Jin, 2020)—suggest that AI-skilled workers are similar to other specialized, high-skilled, high-wage jobs. For example, in terms of the technological and innovative nature of their work, AI-skilled workers could be compared to inventors. Inventors also tend to be highly paid and represent around 0.13–0.24% of the U.S. workforce, which is similar in prevalence to AI workers.[16] Overall, while AI workers form a small fraction of the overall workforce, it is helpful to contextualize their impact against that of executives (Bertrand and Schoar, 2003) and patent inventors (Kline et al., 2019), both of whom are similarly small, high-skilled groups of employees that can nonetheless disproportionately affect firm outcomes.

Second, we document that the increase in AI jobs displays an intuitive distribution across industries. Panel (a) of Figure 2 plots the average share of AI-related workers in the resume data for public firms in each of the 2-digit NAICS sectors, separately for the years 2007–2014 and 2015–2018. Panel (b) repeats the same analysis for the share of AI-related job postings. The figure highlights that the share of AI-skilled jobs (job postings) is highest in the "Information" sector, growing from 0.15% (0.57%) in the early years of 2007–2014 to 0.50% (1.68%) in the later period of 2015–2018. However, almost all sectors see a meaningful increase, supporting the notion that AI is a general purpose technology (Goldfarb et al., 2019). The ability of our measures to pick up AI investments in a broad cross-section of economic sectors highlights a key advantage of our human-capital-based approach.

Third, intuitively, AI investments correlate positively with increased R&D expenditures. For example, changes in the resume-based share of AI workers from 2010 to 2018 display a correlation of 0.27 with changes in log R&D expenditures over the same time period, controlling for industry fixed effects. The pattern of AI-investing firms increasing research and development (R&D) expenditures supports the notion that AI investments involve a great deal of experimentation with applying the new technology (Braguinsky et al., 2020).

Fourth, digging deeper into the skills and jobs with the highest AI-relatedness measures according to our methodology, we observe that our measure is indeed capturing the essence of AI-skilled hiring by firms. The required skills in job postings with the highest AI-relatedness measures, presented in Online Appendix Table A1, are highly AI-specific skills, such as "Tensorflow" and "Random Forests," while general data-analytics-related skills have low AI-relatedness

[16]These estimates come from the USPTO patent data (Babina et al., 2020), where 0.13% is the share of U.S. workers who file patents in a given year, and 0.24% is the share of U.S. workers who file patents over a three-year period.

measures: for example, the measure is equal to 0.04 for "Data Modeling" and 0.03 for "Quantitative Analysis." Similarly, Online Appendix Table A3 shows that the job titles associated with the highest job-level measures of AI-relatedness are all very relevant postings such as "Artificial Intelligence Engineer" (average AI-relatedness measure of 0.497), "Senior Data Scientist - Machine Learning Engineer" (0.394), and "AI Consultant" (0.369). Since we do not require information contained in job titles of job postings to identify AI-related skills and jobs, these patterns provide additional validation that our measure captures relevant AI positions.

As a further validation, it is worth noting the geographic locations of the identified AI jobs. We aggregate firm-level AI hiring of Compustat firms to the commuting zone level and link the commuting-zone-level changes in the share of AI workers from 2010 to 2018 to 2010 commuting zone characteristics from the Census American Community Survey. Online Appendix Figure A2 displays a heat map of the growth in the average continuous job-level AI relatedness measure based on the job postings data from 2010 to 2018 and shows that there is significant variation in AI investments across commuting zones. Online Appendix Figure A3 (a) shows a strong positive relationship between the change in the share of AI workers from 2010 to 2018 and the average commuting-zone-level log wage in 2010. Online Appendix Figure A3 (b) demonstrates that the growth in AI workers is also concentrated in commuting zones with a large fraction of college-educated workers. These patterns are intuitive, given that AI employees tend to be high-skilled technologically-oriented workers, and contrast with investments in robotics, which concentrate in areas with larger shares of manufacturing employment (Acemoglu et al., 2020a).

Finally, in Table 1, we observe a high correlation between our measure of AI investments based on the novel resume data and on the job postings data. The resume data provide several advantages over the job postings data for measuring firms' AI investments. First, the resume data measure actual hiring of AI-skilled labor. For example, if a firm is unable to fill AI-related vacancies, the job postings measure will overstate that firm's investments in AI. Second, human capital on-boarded through acquisitions is captured by the resume data, where employees of acquisition targets are counted as employees of the acquirer subsequent to the acquisition.[17] For these reasons, we focus on the resume-based measure of AI investments in our baseline specifications. Nevertheless, we find high correlations between the two measures and consistent results throughout the remainder of the paper, which alleviates some of the concerns about job postings data in measuring firms' AI talent. This consistency suggests that, in the absence of matched employer-employee data, our methodology offers a good proxy for firms' actual AI hiring using the more widely accessible job postings data.

[17] Industry reports estimate that 90% of firms' investments in AI are internal, with only 10% coming from acquisitions (Bughin et al., 2017).

3.4 Firm-level Determinants of AI Investments

We consider the determinants of AI investments and document that larger firms and firms with higher markups, cash reserves, and R&D tend to invest in AI more aggressively.

Our focus is on understanding the *use* of AI technologies by a wide range of firms, rather than the invention of new AI tools. For that reason, we exclude firms in the tech sector (2-digit NAICS 51 or 54) from our main empirical analyses in this and the following sections.[18] Our main regression sample is comprised as follows. In 2010, there are 3735 U.S.-listed public firms that have non-missing industry codes, positive sales and employment, and are not in the tech sector. Among these firms, 2668 are matched to Cognism,[19] and we further restrict to firms with at least 20 U.S. jobs in both 2010 and 2018 to ensure good coverage of the firm's workforce, which leaves us with 1993 firms.

In Table 2, we examine which ex ante firm characteristics predict future growth in firm-level AI investments. For each measure of AI investments, we estimate the following specification:

$$\Delta ShareAIWorkers_{i,[2010,2018]} = \beta FirmVariable_{i,2010} + IndustryFE + \epsilon_i, \tag{1}$$

where $\Delta ShareAIWorkers_{i,[2010,2018]}$ denotes the change in the share of firm i's AI-related employees from 2010 to 2018. All regressions include 2-digit NAICS industry fixed effects. Here and throughout all subsequent analyses, the $\Delta ShareAIWorkers_{i,[2010,2018]}$ variables are standardized to mean zero and standard deviation one to aid in economic interpretation. $FirmVariable_{i,2010}$ represents one of the ex ante firm characteristics of interest measured as of 2010: log firm sales in column 1, the ratio of cash to total assets (Cash/Assets) in column 2, the ratio of R&D expenditures to sales (R&D/Sales) in column 3, revenue total factor productivity (TFP)[20] in column 4, log markup measured as the log of the ratio of sales to cost of goods sold following De Loecker et al. (2020) in column 5, Tobin's Q defined as market value of assets divided by book value of assets in column 6, market leverage measured as total debt divided by market value in column 7, return on assets (ROA) measured as the ratio of net income plus interest expense to assets in column 8, and firm age in column 9. Column 10 includes all variables in a multivariate specification. We winsorize all continuous variables at 1% and 99% to limit the influence of outliers, although we

[18] In later analyses, we confirm that the main effects of AI spurring firm-level growth are also present in these industries. A complementary analysis of the impact of AI on specifically AI-inventing firms is provided by Alderucci et al. (2020).

[19] Firms that are not matched to Cognism tend to be either ADRs that do not have U.S. employees or smaller firms with few employees.

[20] We use standard methodology to calculate revenue TFP as the residual from regressing log real sales on log employment and log capital, controlling for firm fixed effects and year fixed effects: $\log y_{it} = \mu_i + \mu_t + \alpha_s^l \log(l_{it}) + \alpha_s^k \log(k_{it-1}) + \varepsilon_{it}$. The regression is estimated using OLS separately for each industry. The capital stock is constructed using the perpetual inventory method. The TFP measure is specific to Cobb-Douglas production functions, while sales per worker measure labor productivity for more general production functions.

confirm in untabulated analyses that, empirically, our results are little changed by the winsorization. To account for differences in precision in the measurement of AI investments across firms with different numbers of available observations, the estimating equation is weighted by each firm's number of resumes in 2010.[21]

The results reported in Table 2 highlight that ex ante larger firms experience higher growth in AI investments. A one-standard-deviation increase in log sales in 2010 (which equals 2.1) corresponds to the share of AI workers increasing by 23% of the standard deviation from 2010 to 2018, significant at the 1% level. In addition, firms with higher starting Cash/Assets, R&D/Sales, and markups also see greater investments in AI, consistent with contemporaneous work of Alekseeva et al. (2020). By contrast, revenue total factor productivity, firm valuation (Tobin's Q), market leverage, return on assets, and firm age do not robustly predict future AI investments. In all further regressions, we control for the ex-ante firm characteristics that predict firm AI adoption (size, cash/assets, R&D/sales, and markups). Online Appendix Table A4 shows that the patterns for firm-level demand for AI talent measured with Burning Glass job postings data are consistent with the results using Cognism resume data, reinforcing the high correlations documented in Table 1.

4 AI Investments and Firm Growth

We next document that firms investing in AI technologies grow faster in sales, employment, and market value. We consider and rule out alternative explanations for this result, including reverse causality (e.g., firms on faster growth trajectories invest more in AI) and omitted variables (e.g., concurrent investments in other technologies or demand shocks drive both firm growth and AI investments). Finally, we introduce a novel instrumental variable strategy to estimate the causal effects of AI investments on firm growth.

4.1 Long-differences Results

We begin the analysis by examining whether firms that invest in AI see faster growth from 2010 to 2018. As is standard in settings with slow-moving processes, such as technological progress (e.g., Acemoglu and Restrepo, 2020), our primary specification is a long-differences regression of changes in firm outcomes from 2010 to 2018 on changes in AI investments proxied by the share of AI workers. This strategy is especially well-suited for our setting because AI investments are gradual over time (with 70% of firms onboarding AI workers over a span of multiple years), with

[21]Since the numbers of worker resumes are correlated with firm size, this weighting scheme also roughly weights firms in accordance to their contribution to the economy.

effects that may not be immediate. By taking first differences in independent and dependent variables, the long-differences specification ensures that time-invariant firm characteristics do not drive the results.[22] In Table 3, we report the estimates from the following regression:

$$\Delta FirmVariable_{i,[2010,2018]} = \beta \Delta ShareAIWorkers_{i,[2010,2018]} + Controls'_{i,2010}\gamma + IndustryFE + \epsilon_i, \quad (2)$$

where the main independent variable, $\Delta ShareAIWorkers_{i,[2010,2018]}$, captures the change in the share of AI workers based on the resume data in firm i from 2010 to 2018, standardized to mean zero and standard deviation of one. As in Section 3.4, this analysis focuses on firms in non-tech sectors. $IndustryFE$ are 2-digit NAICS fixed effects. In columns 1, 3, and 5 we include only industry fixed effects to examine the unconditional relationship between changes in AI investments and firm growth. In columns 2, 4, and 6, we include a rich set of controls that are all measured at the start of the sample period in 2010: (i) the initial firm-level characteristics that predict changes in AI investments in Section 3.4 (log sales, cash/assets, R&D/Sales, and log markup) and the log of the firm's total number of jobs[23]; (ii) characteristics of the commuting zones (CZ) where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers); and (iii) the log industry-average wage.[24] Out of the 1993 non-tech firms in the sample in Table 2, 1472 firms have positive sales and employment in 2018, which are necessary to calculate the dependent variables. We further restrict the sample to firms with non-missing control variables throughout, to keep the sample composition stable. This results in a sample of 1052 firms. The results of the regressions without controls are similar when estimated on the entire available sample. Summary statistics on key variables for the main regression sample are provided in Online Appendix Table A5.

In columns 1 and 2 of Table 3, the dependent variable is the firm-level change in log sales from 2010 to 2018. Changes in AI investments are associated with a significant and economically meaningful increase in sales growth: a one-standard-deviation increase in the share of AI workers

[22] A potential concern with the long-differences specification is that it requires AI-investing firms to be present at the beginning (2010) and the end of the sample (2018), which might introduce a sample selection bias. In Section 4.2, we use the full panel data, which does not condition on firms being present over the entire sample period, and find similar effects. Moreover, the industry-level analysis in Section 6 shows that the inclusion of entering and exiting firms has little effect on our results, which would not be the case if the composition of firms changed in an important way.

[23] We control for the log number of jobs to address the concern that the share of AI jobs may be more volatile in firms with fewer total jobs. This control ensures that the variation in the share of AI jobs is between firms with similar total numbers of jobs but different numbers of AI jobs.

[24] When firms span multiple commuting zones, we calculate commuting-zone-level variables as the weighted average, using numbers of BG job postings in each commuting zone as weights, which restricts the sample in the Cognism regression analysis to firms that are also matched to the Burning Glass data. The results are similar in magnitude and economic significance if we only include firm-level controls enumerated in list (i).

over an eight-year period corresponds to an additional 20% growth in sales. In columns 3 and 4, we find a positive effect on employment of a similar magnitude to the effect on sales. This suggests that AI is not yet displacing firms' workforces, at least on net, although we do not rule out the reallocation of labor across different job functions or tasks.[25] Columns 5 and 6 show that firms investing in AI also see increases in their stock market valuations: a one-standard-deviation increase in the share of AI workers is associated with a 23% increase in the firm's market value.[26] It is worth noting that the inclusion of firm-level, location-level, and industry-level controls in even columns (all measured at the start of the sample period in 2010) generally has little effect on the estimated coefficients. This makes it unlikely that the results are driven by ex-ante omitted firm characteristics (Altonji et al., 2005).

The magnitude of the effects in Table 3 is economically meaningful—on the order of a 2% increase in annual sales growth per one-standard-deviation increase in the share of AI workers. Our results provide initial evidence that AI-skilled labor can have a strong positive relationship with firm growth. In this context, our results are consistent with prior evidence that certain key, high-skilled employees—including chief executives, inventors, and entrepreneurs—can have a disproportionate effect on firm outcomes.

The positive relationship between increases in AI investments and firm growth is ubiquitous across different sectors of the economy, reinforcing the notion that AI is a general purpose technology. Online Appendix Table A6 displays the results from regressing changes in log sales and log employment on the change in the share of AI workers, separately for the largest 2-digit NAICS sectors: (i) Manufacturing, (ii) Wholesale and Retail Trade, (iii) Finance, and (iv) the remaining non-tech sectors. While we exclude tech sectors from our main analysis, we find that AI also has an positive relationship with growth for firms in the two tech sectors—Information and Professional and Business Services (see Online Appendix Table A7). Overall, we observe that investments in AI are associated with economically significant increases in firms' operations, and these effects are meaningful across key economic sectors.

However, the benefits from AI investments are not evenly distributed across the firm size distribution. Table 4 shows the relationship between changes in AI investments and firm growth, across terciles of firms by employment in 2010 (within the firm's 2-digit NAICS sector), controlling for initial size and sector-by-size-tercile fixed effects. The effect of AI investments on employment, sales, and market value is monotonically increasing in the firm's initial size. The stronger positive relationship between changes in AI investments and growth among the ex ante larger firms is

[25] In untabulated analyses, we confirm that the results are similar when using changes in employee counts in the Cognism resume data rather than Compustat employment.

[26] Market value is defined as total assets (*at*), minus the book value of common equity (*ceq*), plus the market value of common equity (*prcc_c* times *csho*).

consistent with big data and AI technologies having scale effects that favor large firms, which accumulate large amounts of data as a by-product of their economic activity (Farboodi et al., 2019). Akcigit and Kerr (2018) highlight that larger firms face constraints on their ability to scale due to higher costs of new product innovation. The results in Table 4 suggest that AI may provide a channel through which large firms can combat barriers to innovation and scale by leveraging their data assets. For example, biotech firms that have accumulated large troves of proprietary samples of molecular compounds are able to leverage AI tools to obtain an advantage over competitors.[27]

4.1.1 Robustness

We show that our results are robust to using alternative constructions of the AI measure and address several identification concerns regarding the effects of AI investments on firm growth.

Alternative measures of AI investments. We use the resume-based share of AI workers as our main measure of AI investments because the resume data address two important potential measurement concerns regarding job postings data: (i) the job-postings-based measure captures only firms' demand for AI talent and not their actual ability to hire; and (ii) firms acquire AI expertise through acquisitions, which would not be reflected in job postings but is captured in the Cognism resume data, which reflect actual employees, including those onboarded through acquisitions.

Nevertheless, in the Online Appendix we show that our results remain similar when measuring AI using the Burning Glass job postings data using our methodology discussion in Section 3. Table A8 uses the share of AI-related job postings (defined as job postings with continuous AI-relatedness measure above 0.1); Table A9 uses firm-level average continuous AI-relatedness measures of job postings based on all skills (Panel 1) or refined narrow AI skills (Panel 2), defined in Section 3.1; Table A10 considers alternative cutoffs of 0.05 and 0.15 for defining AI-related job postings. All of these measures yield a positive and significant effect of AI investments, confirming that resume-based and job-postings-based measures are highly correlated and that job postings also provide a useful measure of AI investments.

We next address concerns regarding the skewness of investments in AI. Instead of using standardized measures of AI investments, we also consider dummy variables indicating whether firms' investments in AI are in the top 10 percent or 25 percent of the distribution using our main resume-based measure of AI investments. Online Appendix Table A11 shows that the top 25% of firms in terms of AI investments grow their sales by 30% and the top 10% of firms grow their sales by almost 50% between 2010 and 2018.

Finally, while our measure is centered on internal AI investments, our rich resume data allow

[27]See here for the PitchBook AI & ML Emerging Tech Report 2021.

us to also consider whether firms' use of external AI solutions might affect the interpretation of our results. Even external AI software requires internal data management and implementation guidance by AI-skilled workers to be effective (Fedyk, 2016), and industry reports underscore that AI-skilled labor is the most critical input to successful deployment of AI programs. Nevertheless, we leverage the rich detail of the Cognism resume data to confirm that our approach of focusing on AI workers to identify AI investments is indeed a suitable one. We undertake a deep dive into case studies of individual firms (see Online Appendix A2 for examples) and observe that (i) our measure captures internal AI investments well, and (ii) the use of external AI software solutions (e.g., IBM Watson, IPSoft Amelia) tends to be complementary to internal AI hiring. In addition, we process individual job descriptions and job titles in our resume data for any mention of external AI software (including IBM Watson Studio, Symphony, AyasdiAI, Salesforce Einstein, and about a hundred other key AI-powered solutions) to construct a proxy for firms' reliance on external AI solutions.[28] In Online Appendix Table A12, we confirm that our results are robust to directly including this proxy in our overall measure of AI investments.

Confounding factors. The estimates above may not reflect causal effects of AI investments if contemporaneous changes at AI-investing firms lead to both increased investment in AI and higher firm growth. In Section 4.3, we use an instrumental variable strategy to address the omitted variable bias. Below, we discuss the main confounding factors and provide evidence that our estimates are not driven by these confounders.

First, we address the possibility that investments in AI are correlated with investments in other technologies (e.g., IT). We leverage our detailed data to develop measures of investments in non-AI technologies that parallel the measure of AI investments: for each firm, we measure the percentage of job postings in each year requiring IT-, robotics- or data-related skills that are not specific to AI. In Online Appendix Table A13, we control for growth in: (i) investments in (non-AI) IT, (ii) investments in robots, (iii) investments in non-AI data skills (e.g., "Data Cleaning"), and (iv) investments in non-AI-related data analytics (e.g., "SAS"). Panel 1 uses the resume-based AI measure, and Panel 2 uses the job-postings-based AI measure. The estimated relationship between growth in AI investments and firm growth remains similar with the addition of these controls, confirming that the documented effects on firm growth are specifically driven by AI rather than by other technologies.

Second, AI-investing firms may be experiencing positive demand shocks or be on higher growth trajectories, leading to a positive bias in our estimates. In Online Appendix Table A14,

[28]The Cognism resume data are especially well-suited to capture the use of external technological solutions, given Cognism's emphasis on developing "technographic data" (defined by Cognism as "the technologies that the employee or company is using"). Cognism advertises these data for two purposes: (i) enhancing technology-providers' targeted marketing of their products, and (ii) improving individual firms' understanding of which technologies are used by their competitors.

we control for detailed industry fixed effects to absorb industry-specific shocks. The coefficient on the changes in AI investments remains stable, and the standard error increases as more granular industry controls absorb more of the variation. Moreover, in Online Appendix Table A15, we control for past industry-level and firm-level growth in the decade before our sample period (from 2000 to 2008) and find similar results. In Online Appendix Table A16, we further confirm that the results are robust to the addition of controls for (i) Tobin's Q as of 2010, which proxies for the firm's future growth opportunities, and (ii) state fixed effects, which control for growth opportunities and other potential omitted variables at the state level. Finally, Online Appendix Table A17 estimates a predictive regression of firm growth during the later part of our sample (2015–2020) on growth in AI investments during the earlier part of the sample (2010–2015).[29] The estimates are qualitatively and quantitatively similar to those in Online Appendix Table 3, with milder magnitudes corresponding to the shorter estimation period (growth from 2015 to 2020 rather than 2010 to 2018), pointing against reverse causality driving our results. In the next two sections, we use a dynamic specification and an IV strategy to further address the potential bias from unobserved shocks.

4.2 Dynamic Effects

We augment our long-differences specification by estimating the dynamics of firm growth following AI investments. This analysis not only offers evidence against reverse causality concerns and AI-investing firms being on differential growth trajectories prior to AI investments, but also elucidates the lag between AI investments and their realized effects.

We use firm-level panel data to estimate firm growth dynamically around AI investments in a distributed lead-lag model, which allows for continuous variation in the treatment variable (Stock and Watson, 2015; Aghion et al., 2020). This specification is especially well-suited to our setting, because firms tend to invest in AI on a continuous basis, rather than make lumpy investments in a single year, which precludes us from examining dynamic effects in a standard event-study framework with discontinuous treatment (e.g., before and after a lumpy investment).[30] The standard distributed lead-lag model is specified as:

$$Y_{it} = \sum_{k=-2}^{5} \delta_k \Delta ShareAIWorkers_{i,t-k} + \mu_i + \lambda_{nt} + \theta_{st} + \epsilon_{it} \tag{3}$$

where $\Delta ShareAIWorkers_{i,t-k}$ is the annual change in the share of AI workers from year $t-k-1$

[29] In these regressions, we can use firm growth estimated through 2020, because this specification does not require firm AI data (which end in 2018) to go beyond 2015.

[30] The percentage of AI-investing firms that only invest in a single year is 29.5%, compared to 70.6% for robotics (Humlum, 2019).

to year $t-k$, normalized to mean zero and standard deviation of one, and Y_{it} is either log sales or log employment in year t. We include firm fixed effects μ_i to absorb firm-specific time-invariant factors, and industry-year fixed effects λ_{nt} and state-year fixed effects θ_{st} to control for industry-specific and state-specific trends. Each lead-lag coefficient δ_k captures the cumulative response of the outcome variable in year t to AI investments in year $t-k$, holding fixed the path of AI investments in all other years. As such, specification (3) incorporates both immediate and delayed responses of firm size to firms' AI investments.[31] The estimated coefficients for the leads can be used as a pre-trend test: if firms investing in AI are on similar growth trends as other firms prior to AI investments, δ_k with $k<0$ should be statistically indistinguishable from zero.[32]

Figure 3 reports the coefficients from the lead-lag regressions. The top panel shows that sales increase following AI investments, but not immediately—it takes two to three years for firms to realize the benefits from AI investments. The cumulative effect of a one-standard-deviation increase in annual AI investments on log annual sales is 1.5%–2% and remains steady five years out. This is consistent with the long-differences estimates in Section 4.1, where a one-standard-deviation increase in AI investments is associated with a 20% increase in sales over eight years. The bottom panel shows that AI investments have a similar positive effect on firms' employment. Importantly, there is no evidence of pre-trends in either outcome variable: conditional on the controls we include, firms that invest more in AI in any given year show comparable sales and employment paths in prior years and start diverging only afterwards. This provides additional evidence that our results are not capturing the reverse effect of firm growth on AI investments or the effect of omitted variables placing AI-investing firms on differential growth trajectories, helping to bolster a causal interpretation of our main results.

4.3 Instrumental Variable Estimates

In this section, we instrument firm-level changes in AI investments using firms' exposure to the supply of AI talent from U.S. universities. This helps to isolate variation in firms' AI investments that comes from the supply of AI labor, mitigating potential bias from demand shocks driving both firms' AI investments and growth. The scarcity of AI talent is a key constraint to firms' adoption of AI technologies, and the IV estimates are directly informative about the treatment effects of policies targeting the supply of AI labor and relaxing the constraints of AI adoption. At

[31] For each firm-year observation of sales or employment between 2010 and 2016, we consider five lags and two leads, so that we estimate the cumulative impact of AI investments on firm growth from two years before the investments to five years after the investments. Since the data on AI investments end in 2018, we include only two leads to keep all firm-year observations up to 2016. We obtain similar results when including only one lead or no leads at all.

[32] It is worth noting that, given that the independent variables in this distributed lead-lag model are changes in continuous AI investments instead of period dummies as would be the case in a standard event-study framework, we cannot normalize the estimates to an exact zero for any given period.

the same time, academic research in AI has been ongoing for much longer than the commercial interest in AI. As a result, firms' preexisting connections to AI-strong universities offer an arguably exogenous source of variation in firms' access to the supply of AI talent during the 2010s boom in commercial interest in AI.

In particular, we instrument firm-level changes in AI investments using variation in firms' ex-ante exposure to the supply of AI talent from universities that are historically strong in AI research. The core idea is that the scarcity of AI-trained labor is one of the most important constraints to firms' AI adoption (e.g., CorrelationOne, 2019), and universities that are historically strong in AI research have been able to train more AI-skilled graduates in recent years, enabling firms that typically hire from those universities to more readily attract AI talent. Since commercial interest in AI became widespread only around 2012, we argue (and offer empirical support) that firms' connections to AI-strong universities in 2010 were not driven by the need to hire AI-skilled workers, especially for the sample of non-tech firms that are the focus of this paper. To construct the instrument, we compile two datasets on: (i) the ex-ante strength of AI research in each university, and (ii) firm-university hiring networks. To the best of our knowledge, there is no comprehensive historical data on either of these two aspects. We now briefly discuss the construction of both datasets, while Appendix A provides a detailed discussion of these issues.

To identify universities strong in AI research before 2010, we use data from the Open Academic Graph (OAGv2), which provides the most comprehensive openly available repository of scholarly work since 1870 (Sinha et al., 2015; Tang et al., 2008). We match 689 research institutions in the National Science Foundation's Higher Education Research and Development Survey (HERDS) to researchers in the OAGv2 and work with the field experts at the AI for Good Foundation to identify AI-related publications. We classify each AI researcher based on the share of AI publications in that researcher's overall portfolio, and we classify universities as AI-strong if their number of AI researchers is at the top of the distribution over 2005–2009.

We construct the firm-university hiring networks by leveraging our resume data to observe the universities granting the degrees of each firm's employees.[33] For the firm-university hiring networks to provide the necessary variation for our instrumental variable strategy, different firms need to hire from different sets of universities, and these networks need to be persistent over time. Our data show evidence of both: each firm tends to concentrate its hiring in a small number of universities, and ex-ante networks (i.e., which universities each firm hired from before 2010) strongly predict the universities from which firms hire after 2010 (see Appendix Table 9).

[33] Aggregated to the university-year level, our resume data cover, on average, 59% of all degrees conferred by each university according to IPEDS data, and the number of fresh graduates in the resume data is highly correlated with the total number of degrees conferred (correlation=0.73) in the IPEDS data. Confirming the relevance of our measure of AI-strong universities, Appendix Figure 5 shows that the increase in AI-trained graduates during the 2010s was much more pronounced in ex-ante AI-strong universities than in non-AI-strong universities.

We define our instrument for each firm i as: $IV_i = \sum_u s_{iu}^{2010} AIstrong_u$, where s_{iu}^{2010} is the share of STEM workers in firm i in 2010 who graduated from university u, and $AIstrong_u$ equals one if university u is identified as an AI-strong university based on pre-2010 publications.[34] We use pre-2010 publications to measure AI-strong universities because research in AI has flourished in universities long before 2010, while commercial use of AI began after 2010. Thus, post-2010 publications may be affected by demand for AI from the firms that universities are connected to, whereas pre-2010 publications are an arguably exogenous measure of universities' AI talent.

A key concern with our instrument is that AI-strong universities may also be different in other ways. First, if universities strong in AI research are also strong in the broader field of computer science (CS), producing more CS-skilled graduates, this might affect firm outcomes through channels other than AI investments. Second, if AI-strong universities are ranked highly in general, then high quality firms—who are likely to grow regardless of AI—may hire from AI-strong universities purely by hiring from highly-ranked universities. To address these concerns, we control for firms' ex-ante exposure to CS-strong universities and top-ranked universities. In particular, we construct analogous measures of firms' ex-ante exposure to CS-strong and top-10 universities: $\sum_u s_{iu}^{2010} CSstrong_u$ and $\sum_u s_{iu}^{2010} Top10_u$, where $CSstrong_u$ is the average pre-2010 share of (non-AI) CS researchers at university u, and $Top10_u$ equals one if a university is among the top 10 universities ranked by the U.S. News & World Report.

Another potential concern regarding our instrument is that firms that anticipated the surge in demand for AI may have started building their connections to AI-strong universities before 2010, making firm-university hiring networks in 2010 endogenous to firms' demand for AI-trained students. However, this runs counter to the lack of both commercial interest in AI by firms and AI-skilled graduates by universities prior to 2010 (see Appendix Figure 5). Moreover, we confirm empirically that firms connected to AI-strong universities in 2010 did *not* increase their share of hired fresh graduates from those universities from 2005 to 2010 (see Appendix Table 10).

Appendix Table 12 shows the first-stage results. We control for industry fixed effects and exposure to CS-strong and top-10 universities in all columns. We sequentially add (i) baseline controls (firm-, industry-, and commuting-zone-level controls), (ii) pre-period firm sales and employment growth between 2000 and 2008 to address unobservable firm characteristics that might simultaneously drive firms' growth trajectories and their hiring of AI workers, and (iii) state fixed effects to control for local labor market characteristics that might drive both firms' AI hiring and and their growth. The instrument has a strong first stage with F-statistics above 10 for all specifications and above 20 when all controls are included. Online Appendix Figure A4 plots the reduced-form rela-

[34] We use firm-university hiring networks based on STEM workers to account for potential segmentation in firms' hiring networks, where business employees may be hired from different universities than technically skilled employees. However, empirically, firm-university hiring networks constructed from all workers yield similar results.

tionship between the instrument and firm growth with all controls included. For all three outcome variables (sales, employment, and market value), we see a strong positive relationship between firms' ex-ante exposure to AI-strong universities and subsequent growth. In contrast, Appendix Table 11 shows that firms that are more exposed to AI-strong universities are not growing faster before 2010. This is consistent with the exclusion restriction that the instrument only affects firm growth through firms' AI investments after 2010.

Table 5 presents the 2SLS estimates. The results show a robust and significant effect of AI investments on sales (columns 1–4), employment (columns 5–8), and market value (columns 9–12). When all controls are included, a one-standard-deviation increase in AI investments leads to an increase in sales of 32% and increases of 34% in both employment and stock market valuation. The magnitudes are about 50% larger than OLS estimates, which may be due to measurement error or a negative bias from firms with lower opportunity costs of innovation and lower growth prospects investing in AI. It is important to note, however, that the OLS and IV coefficients are not statistically different. This suggests that the difference between the point estimates could also be driven by estimation error.

5 Mechanisms

We examine the drivers of AI-fueled firm growth by considering the two non-mutually-exclusive mechanisms detailed in Section 1. We document that AI-investing firms are able to significantly increase their product innovation and find no evidence of reductions in operating costs.

5.1 AI as a Driver of Product Innovation

As we outline in Section 1, AI can contribute to firm growth via product innovation by: (i) facilitating the creation of new and improved products, and (ii) increasing product scope through improved tailoring of products to customer tastes. To explore this empirically, we need firm-level data on products and services, which are challenging to obtain, especially across different sectors. We overcome this challenge by using three proxies for firms' product innovation.

First, we examine whether AI-investing firms experience increases in trademarks, which are registered whenever new products or services are ready for commercialization and therefore offer a good proxy for the creation of new products and services (Hsu et al., 2021). Columns 1 and 2 in Table 6 present the results from long-differences regressions of changes in firms' USPTO trademarks against growth in their AI investments, showing that AI-investing firms significantly increase their trademark portfolios. A one-standard-deviation increase in the share of AI workers

is associated with 15% more trademarks.[35] Second, columns 3 and 4 reveal a similar relationship between AI investments and the number of product patents, which are patents specifically focusing on product innovations.[36] While trademarks are registered with the creation of new products, product patents reflect both new product creation and innovations in the quality of existing product lines. We find that a one-standard-deviation increase in the share of AI workers over eight years corresponds to a 23% increase in the number of product patents.

Finally, we build a measure of changes in firms' product mix based on the self-fluidity measure in Hoberg et al. (2014). Using firm 10K filings, Hoberg et al. (2014) take the cosine similarity between word vectors describing a firm's product offerings in two adjacent years to measure the extent to which the firm's product offerings changed in a given year. These changes reflect both the creation of new products and the tailoring of existing products to evolving consumer tastes.[37] In columns 5 and 6, we find that growth in AI investments is associated with increased changes in firms' product mix from 2010 to 2018. For robustness, Online Appendix Table A18 shows that there is also a positive relationship between the job-postings-based measure of AI investments and changes in product innovation.

Online Appendix Table A19 shows that the instrumented AI investments also have a positive effect on the number of trademarks, the number of product patents, and the change in product offerings (although not always significant). Overall, the results point towards firms utilizing AI to expand product variety and customization, consistent with surveys of corporate executives, who highlight product improvement and creation as top uses of AI (see here).

5.2 AI as a Driver of Lower Operating Costs

We next test whether the increase in firm growth from AI investments could reflect AI technologies lowering firms' operating costs and increasing firm-level productivity. First, in columns 1 to 4 of Table 7 we look at costs directly by considering how growth in firms' AI investments relate to changes in costs of goods sold (COGS) and operating expenses. AI investments are associated with increases in costs that are similar in magnitude to the growth in firm sales, suggesting that

[35]The dependent variable is the change in log(1 + number of trademarks) from 2010 to 2018, so that the regression takes into account firms with zero trademarks in either 2010 or 2018. The results are also robust to using the inverse hyperbolic sine transformation (i.e., $\ln(x + \sqrt{(1 + x^2)})$). The regression sample is smaller than our baseline sample, because not all public firms file trademarks (we include firms with at least one trademark in 2009–2018).

[36]See Ganglmair et al. (2021) for the methodology to distinguish between product patents and process patents. The regression sample is smaller than our baseline sample, because not all public firms file patents, and we only include firms with at least one patent during 2005–2018. The dependent variable is the change in log(1 + number of product patents) from 2010 to 2018.

[37]We use the same word vectors as Hoberg et al. (2014) and construct our measure as follows: for each year, we calculate the angle between the two word vectors indicating firms' product offerings in that year and the previous year. For example, the measure equals 0 if the product offerings remain exactly the same and $\pi/2$ if the product offerings change completely. We sum up of angle of each year over eight years from 2010 to 2018 to measure the total change in firms' product portfolios from 2010 to 2018.

AI is not associated with lower operating costs.

Second, columns 5 to 8 of Table 7 consider two measures of productivity: sales per worker (i.e., labor productivity) and revenue total factor productivity (TFP). The relationship between AI investments and either productivity measure is negative and insignificant. The lack of growth in labor productivity is consistent with the results in Section 4 that AI investments predict similar increases in sales and employment, challenging the view that the primary effect of AI is to replace jobs.[38] Furthermore, in columns 9 and 10, we bring another proxy for efficiency gains that complements revenue-based measures of productivity: process patents, which reflect process innovations and potential improvements in efficiency. We find a zero relationship between AI investments and process innovation, in contrast to the positive increase in product patents documented in Table 6. In Online Appendix Table A20, we also find similar insignificant effects on productivity measures and process patents using the job-postings-based AI measure.

Overall, we find that AI technologies benefit firms through product innovations rather than through reductions in operating expenses or improvements in productivity. This contrasts with previous general purpose technologies, such as electricity, which led to rapid productivity gains (Fizsbein et al., 2020). This juxtaposition of results is consistent with Acemoglu et al. (2022), who use the U.S. Census data and find no correlation between artificial intelligence and labor productivity, but find positive correlations with productivity effects for other technologies such as robotics and specialized software. Our evidence also supports the findings in Gutiérrez and Philippon (2019) that the productivity growth of superstar firms has declined in recent years.

One potential explanation for the lack of productivity growth is the productivity J-curve proposed by Brynjolfsson et al. (2020). In particular, productivity growth from investing in general purpose technologies may be initially underestimated, because capital and labor are spent to accumulate unmeasured output in the form of intangibles that complement the new technology. In Online Appendix Table A21, we examine the effect of changes in AI investments during the first half of the period (2010–2014) on productivity growth through 2018 and do not find any significant positive effect. Hence, even with a lag of a few years, AI investments are not yet associated with productivity improvements. Besides, while the productivity J-curve reflects forgone measurable output in the short run, we find a significant and positive effect on sales growth two to three years following AI investments. Our evidence suggests that at least so far, AI mostly stimulates firm growth through product innovation. This is likely due to the unique features of AI technologies outlined in Section 1: the ability to make predictions based on big data reduces the uncertainty

[38]It is worth noting that both sales per worker and revenue TFP are revenue-based measures of productivity and may not fully reflect actual physical productivity. For example, sales per work and revenue TPF may provide downward-biased estimates of actual productivity changes if quantities produced increase to such an extent that lower prices are charged (Foster et al., 2008; Garcia-Marin and Voigtländern, 2019; Caliendo et al., 2020). To consider this possibility, in untabulated analyses we find that there are no changes in AI-investing firms' markups.

of exploration (Cockburn et al., 2018), facilitates the discovery process for new or better products, and enables the tailoring of products to customer tastes. These findings align with recent work documenting that investments in technologies in recent years are associated with increased scale of the firm but no productivity gains (Aghion et al., 2019; Curtis et al., 2021; Hirvonen et al., 2021).

6 AI Investments and Industry-level Outcomes

To shed light on the potential aggregate effects of AI, we examine the relationship between industry-level variation in AI investments and: (i) industry growth; (ii) industry concentration.

While AI-investing firms grow faster, the gains in industry sales and employment may be zero-sum if the use of AI technologies creates a business-stealing effect on competitors (Bloom et al., 2013). For example, negative spillovers have been shown to dominate positive firm-level effects in the case of robotics, leading to an overall negative effect on aggregate employment Acemoglu et al. (2020a); Benmelech and Zator (2022). Hence, signing the aggregate effect of AI investments is an empirical question. We estimate the following long-differences regression at the industry level:

$$\Delta \ln y_{j,[2010,2018]} = \gamma \Delta ShareAIWorkers_{j,[2010,2018]} + IndustrySectorFE + \epsilon_j \tag{4}$$

where $\Delta \ln y_{j,[2010,2018]}$ is the change in total sales or employment for all Compustat firms (including those that entered the sample after 2010 or exited before 2018) in 5-digit NAICS industry j, and $\Delta ShareAIWorkers_{j,[2010,2018]}$ is the change in the share of AI workers among Compustat firms in industry j from 2010 to 2018. Analogously to the firm-level tests, the regressions are weighted by the total number of resumes in each industry in 2010.

Columns 1 to 4 of Table 8 show that AI investments are associated with a robust increase in employment and sales at the industry level. Odd columns estimate the unconditional relationship (with 2-digit NAICS fixed effects only), and even columns add controls for log employment, log sales, and log average wages at the industry level in 2010. For example, with the full set of controls, a one-standard-deviation increase in the industry-level share of AI workers in the resume data is associated with a 22.0% increase in sales and a 26.0% increase in employment. Importantly, in Online Appendix Table A22, we show that the results remain similar when we restrict the sample to firms that are in the Compustat sample both in 2010 and 2018 (i.e., excluding entrants and exits). This indicates that sample selection issues are not driving our main results for publicly traded firms. While we cannot speak to growth effects outside of publicly traded firms (where sales data are not reported), the fact that our effects concentrate among the largest firms in the Compustat sample (Table 4) suggests that the net effects on industry growth of all (public and

private) firms are likely milder than those documented in Table 8.[39]

We next examine whether the higher AI-fueled growth among larger firms is substantial enough to translate into increased industry concentration. We link industry-level growth in AI investments to contemporaneous changes in industry concentration from 2010 to 2018. Following Autor et al. (2020), we use the Herfindahl-Hirschman Index (HHI) to measure industry concentration. To examine winner-take-most dynamics, we also consider the fraction of sales accruing to the largest firm in each 5-digit NAICS industry among the Compustat firms. Columns 5 to 8 of Table 8 show a robust positive relationship between industry-level growth in AI investments and changes in industry concentration. It is worth noting that our concentration results are based on the sample of Compustat firms; to the extent that AI-fueled growth is concentrated in large firms (Table 4), the overall effect on industry concentration is likely to be even greater.

For robustness, in Online Appendix Table A23, we use the industry-level share of AI-related job postings in the Burning Glass data as the independent variable and find similar positive relationships between AI investments and industry growth and industry concentration.

Overall, our results support the argument by Crouzet and Eberly (2019) that investments in intangible assets are responsible for the rise in industry concentration observed in the U.S. data. Our results suggest that, as a general purpose technology that can be applied across many industries, AI has the potential to further increase concentration across a broad range of industries by facilitating product innovation and the expansion for the largest firms.

7 Conclusion

In this paper, we study how firms invest in and benefit from one of the most important new technologies of the last decade—artificial intelligence. We introduce a novel measure of investments in AI technologies at the firm level using two detailed datasets on human capital: resume data from Cognism, which reveal the actual composition of each firm's workforce, and job postings from Burning Glass Technologies, which indicate each firm's demand for particular skills. Our unique measure allows us to examine both the determinants and the consequences of AI investments by firms across a wide range of sectors. We find a positive feedback loop between AI investments and firm size: AI investments concentrate among the largest firms, and as firms invest in AI, they grow larger, gaining sales, employment, and market share. This AI-fueled growth does not appear to stem from cost-cutting; instead, AI-investing firms expand through product innovation and increased product offerings.

[39] A caveat with these results is that the Compustat sample assigns each firm to a single main industry, even for firms that might have operations in several industries. This caveat is unlikely to affect the interpretation of our results, given that prior research using U.S. Census micro data shows that for a typical U.S. public firm the large majority of its operations fall within one main industry (Babina, 2020).

Our findings highlight important differences between the adoption of AI technologies and the adoption of information technology (IT) in the 1980s and 1990s.[40] Much of the previous literature finds that IT investments were associated with economically large productivity increases but mixed results on firm growth measures such as market share. By contrast, we observe increased growth for AI-investing firms, along with increased product innovation, but no evidence (yet) of higher firm-level productivity. Our results also show higher AI adoption and larger gains from AI investments for larger firms, which contrasts with prior work on diffusion patterns for IT (Hobijn and Jovanovic, 2001). These differences underscore the distinctive features of AI relative to previous waves of IT: as a prediction technology, AI facilitates product innovation and creates new business opportunities by enabling firms to learn better and faster from big data.

Our findings imply that the benefits from AI depend to a large extent on who owns big data—the key input to AI technologies (Fedyk, 2016). While data are non-rival (data can be used by any number of firms simultaneously), recent theoretical work suggests that, fearing creative destruction, firms may choose to hoard data they own, leading to inefficient use of nonrival data; and that giving the data property rights to consumers can generate allocations that are close to optimal (Jones and Tonetti, 2020). While our empirical work does not directly speak to the optimality of data ownership, our results suggest that AI contributes to the increase in industry concentration and the rise of "superstar" firms documented in recent work (Gutiérrez and Philippon, 2017; Autor et al., 2020). Further understanding how AI affects production processes, corporate strategies, and the organizational structure of firms and assessing the distribution of gains from investing in AI technologies across firms and workers are fruitful avenues for future research.

[40]See Dedrick et al. (2003) and Cardona et al. (2013) for reviews of that literature.

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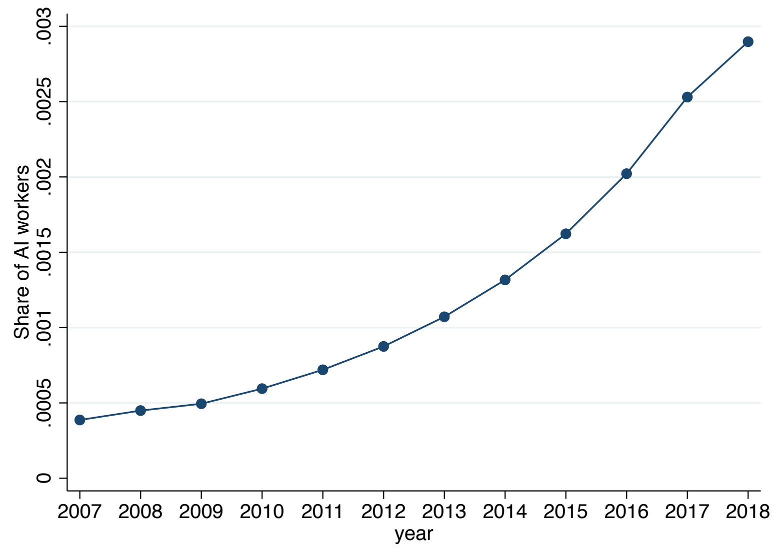
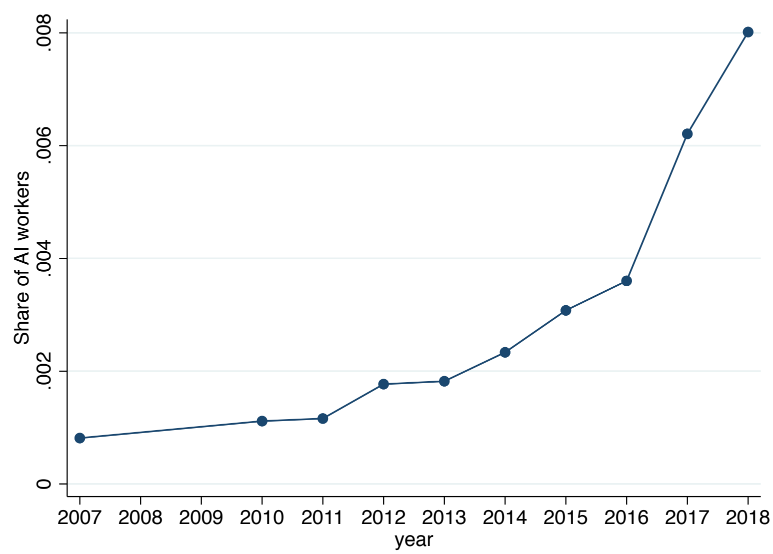
Figure 1. Time Series of AI Investments

This figure shows the time series of the two measures of AI investments. Panel (a) shows the fraction of all employees (across all public firms) in a given year who are classified as holding directly AI-related positions in the Cognism resume data from 2007 to 2018. Panel (b) reports the fraction of job postings with continuous AI measure above 0.1 for 2007 and 2010–2018, based on Burning Glass data with employer firms matched to public firms in Compustat.



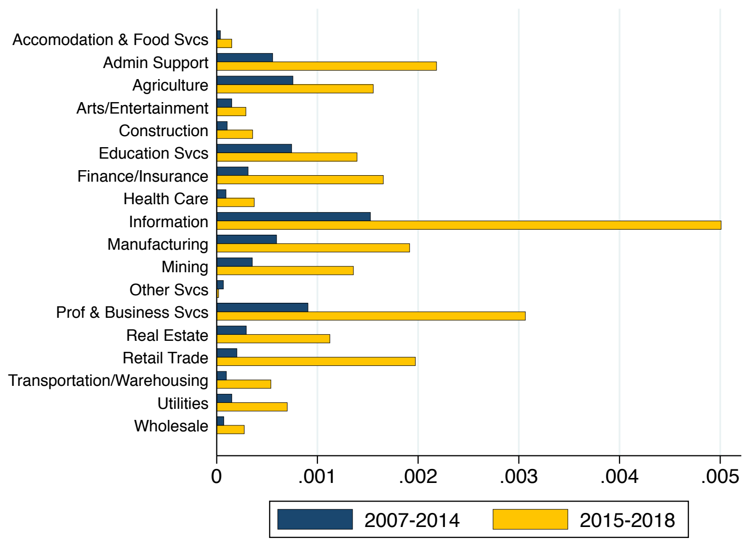
(a) Resume data (Cognism)



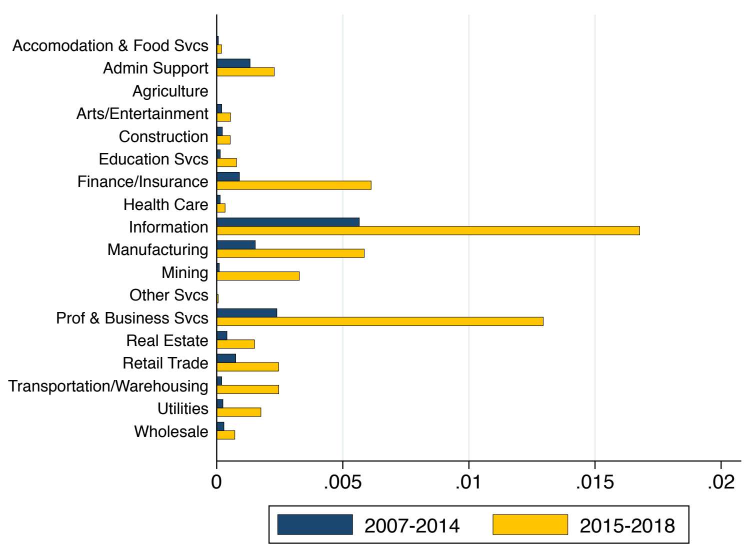
(b) Job posting data (Burning Glass)

Figure 2. AI Investments by Industry Sector

This figure presents the average share of AI jobs at the industry level, based on the sample of public firms. For each sector (based on NAICS-2 digit industry codes), we compute the fraction of AI-related employees in the resume data (in Panel (a)) and the average share of AI-related job postings (with job-level continuous AI measure above 0.1) across all job postings (in Panel (b)). The statistics are computed across all public firms in each sector across two sub-periods: 2007–2014 and 2015–2018.



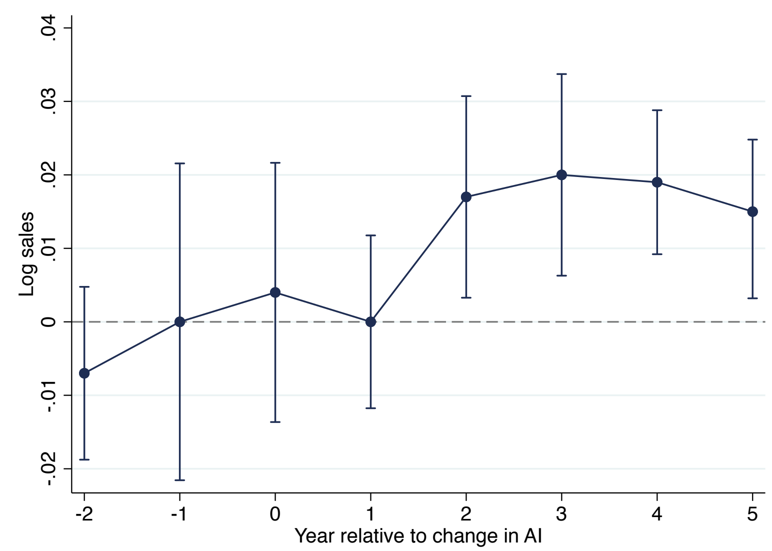
(a) Resume data (Cognism)



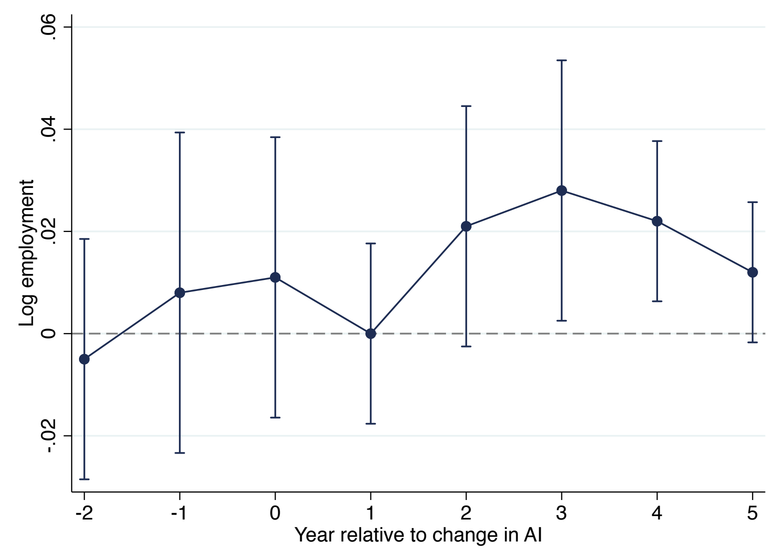
(b) Job posting data (Burning Glass)

Figure 3. AI Investments and Firm Growth Over Time

This figure plots the coefficients from the distributed lead-lag model. The dependent variable is annual log sales in Panel (a) and log employment in Panel (b). The independent variable is the annual change in the share of AI workers in Cognism resume data, standardized to have a mean of zero and a standard deviation of one. Regressions include firm-level sales (or employment) observations between 2010 and 2016 and control for firm fixed effects, 2-digit NAICS industry-by-year fixed effects, and state-by-year fixed effects. Regressions are weighted by the number of workers in Cognism resume data. The vertical bars indicate 95% confidence intervals. Standard errors are clustered at the 5-digit NAICS level.



(a) Sales



(b) Employment

Table 1. Correlations between Job-posting-based and Resume-based AI Measures

This table reports, for each year from 2010 to 2018, the Spearman rank correlations between three pairs of firm-level variables: (i) the absolute number of AI job postings in Burning Glass against the absolute number of AI employees in resumes from Cognism; (ii) the fraction of employees classified as AI-related in the two datasets; and (iii) the fraction of AI employees in Cognism against the average continuous AI measure in Burning Glass. Panel 1 shows raw correlations, and Panel 2 displays correlations conditional on industry sector fixed effects and the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes and job postings), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). All correlations are computed over the cross-section of firms with at least 20 total employees in the Cognism resume data in each year of the sample.

Panel 1: Raw Correlations

	Correlations between:		
Year	Numbers of AI jobs	Fractions of AI Jobs	Cognism fraction & BG continuous measure
2010	0.320	0.272	0.374
2011	0.341	0.288	0.390
2012	0.338	0.291	0.388
2013	0.424	0.363	0.447
2014	0.468	0.410	0.484
2015	0.474	0.405	0.496
2016	0.503	0.421	0.499
2017	0.564	0.474	0.531
2018	0.574	0.484	0.538

Panel 2: Correlations Conditional on Baseline Controls

	Correlations between:		
Year	Numbers of AI jobs	Fractions of AI Jobs	Cognism fraction & BG continuous measure
2010	0.825	0.650	0.470
2011	0.822	0.622	0.476
2012	0.801	0.583	0.487
2013	0.784	0.569	0.498
2014	0.757	0.526	0.551
2015	0.729	0.467	0.513
2016	0.702	0.475	0.501
2017	0.687	0.507	0.510
2018	0.670	0.502	0.513

Table 2. Firm-level Determinants of Resume-based AI Investments

This table reports the coefficients from regressions of cross-sectional changes in AI investments by U.S. public firms (in non-tech sectors) from 2010 to 2018 on the following ex-ante firm characteristics measured in 2010: log sales in column 1, cash/assets in column 2, R&D/sales in column 3, revenue TFP in column 4, log markup measured following De Loecker et al. (2020) in column 5, Tobin's Q in column 6, market leverage in column 7, return on assets (ROA) in column 8, and firm age in column 9. The dependent variable is the growth in the share of AI workers from 2010 to 2018 using the resume data from Cognism. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. The dependent variable is normalized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share of AI Workers, 2010–2018									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.108***									0.151***
	(0.028)									(0.026)
Cash/Assets 2010		3.819***								1.957***
		(1.140)								(0.516)
R&D/Sales 2010			3.607***							2.144**
			(1.225)							(0.840)
Revenue TFP 2010				1.343						-0.407
				(0.995)						(0.256)
Log Markup 2010					0.401*					0.375
					(0.220)					(0.258)
Tobin's Q 2010						0.134***				-0.030
						(0.049)				(0.074)
Market Leverage 2010							-0.873			0.142
							(0.644)			(0.342)
ROA 2010								1.248		1.335
								(0.830)		(0.813)
Firm Age 2010									-0.003	-0.001
									(0.004)	(0.002)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.154	0.301	0.171	0.148	0.144	0.194	0.127	0.130	0.120	0.367
Observations	1,993	1,993	1,993	1,818	1,992	1,653	1,863	1,972	1,993	1,539

Table 3. AI Investments and Firm Growth: Long-differences Estimates Using the Resume-based AI Measure

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). We consider three measures of firm growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). The dependent variables are measured as growth from 2010 to 2018. The main independent variable is the growth in the share of AI workers (based on the resume data) from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.204***	0.203***	0.240**	0.217***	0.232**	0.224***
	(0.070)	(0.061)	(0.097)	(0.078)	(0.094)	(0.078)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.225	0.428	0.239	0.417	0.222	0.364
Observations	1,051	1,051	1,051	1,051	1,009	1,009

Table 4. Heterogeneous Relationship between AI Investments and Firm Growth by Initial Firm Size Using the Resume-based AI Measure

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on contemporaneous changes in AI investments among US public firms (in non-tech sectors), separately for each tercile of initial firm size. Firms in each 2-digit NAICS sector are divided into terciles based on employment in 2010. We consider three measures of firm-level growth for the dependent variable: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). The main independent variable is the growth in the share of AI workers (based on the resume data) from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector by initial firm size tercile fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers*Size Tercile 1	0.046**	0.001	0.041**	-0.013	0.059**	0.019
	(0.023)	(0.020)	(0.018)	(0.027)	(0.028)	(0.041)
Δ Share AI Workers*Size Tercile 2	0.209***	0.173***	0.208***	0.164***	0.192***	0.157***
	(0.051)	(0.047)	(0.045)	(0.056)	(0.042)	(0.050)
Δ Share AI Workers*Size Tercile 3	0.225***	0.215***	0.261**	0.227***	0.252**	0.237***
	(0.077)	(0.067)	(0.105)	(0.083)	(0.104)	(0.088)
NAICS2*Size tercile FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.248	0.426	0.254	0.430	0.213	0.341
Observations	1,043	1,043	1,043	1,043	1,002	1,002
T-test statistic	3.8	8.9	3.8	7.4	4.0	8.7
T-test p value	0.053	0.003	0.053	0.007	0.046	0.004

Table 5. AI Investments and Firm Growth: IV Estimates Using the Resume-based AI Measure

This table estimates the relationship between AI investments and firm growth from 2010 to 2018 for U.S. public firms (in non-tech sectors), where firm AI investments are instrumented with ex-ante firm-level exposure to AI-skilled graduates from AI-strong universities. The independent variable is the change in the share of AI workers from 2010 to 2018 based on the resume data. Regressions are weighted by the number of Cognism resumes in 2010 (see the definition of the instrument in Section 4.3 and the details of instrument construction in Appendix A). The independent variable and the instrument are standardized to mean zero and standard deviation of one. We consider changes in log sales in columns 1 to 4, log employment in columns 5 to 8, and log market value in columns 9 to 12. All specifications control for industry sector fixed effects and ex-ante exposure to universities that are strong in computer science research as well as top 10 universities. Columns 2–4, 6–8, and 10–12 also control for the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Columns 3–4, 7–8, and 11–12 additionally control for firm-level changes in log sales and log employment from 2000 to 2008. Columns 4, 8, and 12 add state fixed effects. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. The first-stage F-statistics of the instrument are reported for all specifications. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales				Δ Log Employment				Δ Log Market Value			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	0.359***	0.516***	0.475***	0.316**	0.465***	0.764***	0.624***	0.339**	0.445***	0.554***	0.494***	0.344*
	(0.098)	(0.122)	(0.140)	(0.152)	(0.151)	(0.223)	(0.194)	(0.164)	(0.128)	(0.150)	(0.172)	(0.182)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
CS Control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Baseline Controls	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Control Pre-trend	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
State FE	N	N	N	Y	N	N	N	Y	N	N	N	Y
F Statistic	12.8	17.7	15.4	21.0	12.8	17.7	15.4	21.0	12.9	18.1	15.3	21.8
Observations	1,001	1,001	777	773	1,001	1,001	777	773	963	963	753	746

Table 6. AI Investments and Product Innovation Using the Resume-based AI Measure

This table reports the coefficients from long-differences regressions of the changes in measures of product innovation from 2010 to 2018 on the contemporaneous changes in AI investments by U.S. public firms (in non-tech sectors). The dependent variables are the change in log(1+number of trademarks) in columns 1 and 2; the change in log(1+number of product patents) in columns 3 and 4; and the change in the product mix in columns 5 and 6. Product patents are patents with over 50% of the claims being product claims, following the categorization in Ganglmair et al. (2021). The change in the product mix is measured as the sum of annual changes from 2010 to 2018, where each annual change is the angle between the two word vectors indicating firms' product offerings in that year and the previous year (the word vectors are constructed as in Hoberg et al. (2014). The main independent variable is the resume-based measure of the growth in the share of AI workers from 2010 to 2018, which is standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Number of Trademarks		Δ Log Number of Product Patents		Change in Product Mix	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.144**	0.152**	0.221***	0.229***	0.148***	0.111***
	(0.065)	(0.077)	(0.035)	(0.039)	(0.036)	(0.035)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Observations	550	550	618	618	957	957

Table 7. AI Investments and Operating Costs Using the Resume-based AI Measure

This table reports the coefficients from long-differences regressions of changes in firm operating costs and firm productivity from 2010 to 2018 on contemporaneous changes in AI investments by U.S. public firms (in non-tech sectors). The main independent variable is the change in the share of AI workers (based on the resume data) from 2010 to 2018, standardized to mean zero and standard deviation of one. We look at two measures of operating costs: log COGS in columns 1 and 2 and log operating expenses in columns 3 and 4. We consider two measures of productivity: log sales per worker (columns 5–6) and revenue TFP (columns 7–8). Revenue TFP is the residual from regressing log revenue on log employment and log capital (constructed using the perpetual inventory method), with separate regressions for each industry sector. In columns 9 and 10, the dependent variable is the change in log(1+number of process patents), where process patents are patents with over 50% of the claims being process claims, following the categorization in Ganglmair et al. (2021). Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, and 8 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log COGS		Δ Log Operating Expense		Δ Log Sales per Worker		Δ Revenue TFP		Δ Log Number of Process Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.197***	0.183***	0.207***	0.205***	-0.036	-0.014	-0.049	-0.024	-0.011	-0.009
	(0.052)	(0.047)	(0.066)	(0.057)	(0.055)	(0.041)	(0.046)	(0.037)	(0.039)	(0.071)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.219	0.394	0.242	0.427	0.244	0.395	0.222	0.350	0.698	0.755
Observations	1,051	1,051	1,051	1,051	1,051	1,051	976	976	618	618

Table 8. AI Investments and Changes in Industry Growth and Concentration Using the Resume-based AI Measure

This table reports the coefficients from industry-level long-differences regressions of the changes in industry sales, employment, and concentration on contemporaneous changes in industry-level AI investments. All industry-level variables are calculated for all firms in Compustat (regardless of whether they are in our main regression sample in Table 3 or not). Each observation is a 5-digit NAICS industry, and (as in our main analysis) we exclude tech sectors. The independent variable is the change in the share of AI workers (based on the resume data) from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the total (industry-level) number of Cognism resumes. The dependent variables are the changes, from 2010 to 2018, in log total sales in columns 1 and 2, log total employment in columns 3 and 4, the Herfindahl-Hirschman Index (HHI) in columns 5 and 6, and the market share of the top firm in an industry in columns 7 and 8. All specifications control for industry sector fixed effects. Regressions in columns 2, 4, 6, and 8 also include industry-level controls for log total employment, log total sales, and log average wage in 2010. Standard errors are robust against heteroskedasticity and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log Sales		Log Employment		HHI		Top Firm Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.190***	0.220***	0.205***	0.260***	0.022**	0.025***	0.015*	0.018**
	(0.067)	(0.062)	(0.071)	(0.069)	(0.008)	(0.009)	(0.008)	(0.009)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Observations	275	275	275	275	267	267	267	267

A Appendix on Instrument Construction

We instrument firm-level AI investments using variation in firms' ex-ante exposure to the supply of AI-trained graduates from universities that are historically strong in AI. The core idea is that the scarcity of AI-trained labor is one of the most important barriers to firms' AI adoption (e.g., CorrelationOne (2019)). Universities are a key source of skilled labor, and universities historically strong in AI research are able to train more AI-skilled graduates following the wide-spread rise of commercial interest in AI in the 2010s. This enables firms with more ex-ante connections to AI-strong universities (e.g., via alumni networks) to more readily attract AI talent from those universities in the 2010s. It is important to note that while AI research flourished in universities long before 2010 (research in AI and machine learning goes back to the 1950s), commercial interest in AI applications started around 2012, driven by rapid accumulation of data, decreasing costs of computation, and methodological advances in applying techniques such as deep learning.[41] Moreover, universities did not set up specialized data science programs until the mid-2010s. For example, Columbia's Data Science Institute (described as a "*trailblazer in the field*"; see here) was established in 2012. Therefore, in 2010, firms' connections to AI-strong universities were not driven by the need to hire AI-skilled workers, but rather by other pre-existing connections such as alumni networks (e.g., the CEO having graduated from a particular university), especially for the sample of non-tech firms that are the focus of this paper.

To construct the instrument, we need two different datasets. The first is a measure of the strength of AI research in each university in the pre-period. The second, even more difficult to construct, is a measure of firm-university hiring networks in the pre-period. To the best of our knowledge, there is no comprehensive historical data on either of these two aspects. To construct the first measure, we group all universities into those that are ex-ante strong in AI research and those that are not, based on the number of researchers producing AI-related publications in each university before 2010. A key concern with this measure for our instrument is that AI-strong universities are likely to also be strong in the broader field of computer science (CS), producing more CS-skilled graduates, which might affect firm outcomes through channels other than AI investments. To address this concern, we also collect information on the number of CS researchers in each university in each year to be included as a control. To construct the second measure (firm-university hiring networks), we leverage our resume data to observe which universities the stock of a given firm's employees as of 2010 graduated from. To validate the data, we also measure: (i) the number of fresh graduates in each year from each university hired by each firm to confirm that ex-ante firm-university networks predict ex-post hiring, and (ii) the number of AI-trained graduates from each university to validate our premise that ex-ante AI-strong universities produce

[41] A brief history of AI research can be found here.

more AI-trained graduates following the increase in commercial interest in AI.

Data Construction. First, to identify universities that are ex-ante strong in AI, we use data from the Open Academic Graph (OAGv2) to measure AI-related publications associated with each university. OAGv2 provides a unified view of two large-scale databases of academic paper metadata, abstracts, citations, and author links: (i) the Microsoft Academic Graph (part of the Microsoft Academic Service infrastructure in Sinha et al. (2015)), and (ii) ArnetMiner (Tang et al., 2008). Together, these two datasets provide the most comprehensive openly available repository of scholarly work starting from the 1870s and allow us to track research articles and faculty across the near-universe of academic and commercial institutions. The Open Academic Graph contains hundreds of millions of papers from 366M distinct author names and lists author affiliations where available. We use a keyword-based matching procedure to link 689 research institutions (or 99%) in the Higher Education Research and Development Survey (HERDS) data to faculty information in the OAGv2. HERDS data are collected by the National Science Foundation and cover all universities in the U.S. that have at least $150,000 in R&D expenditures in each fiscal year. Our strict matching procedure requires that the full formal university name, or an official shortened variant thereof, be found in full form within the institutional affiliations in the OAGv2 paper metadata files, with only common "stop-words" (such as "and," "the," and "in") removed from both sides of the match. A manual review of the resulting linked data shows over 96% precision in matching author affiliations from the Open Academic Graph to HERDS data, with the remaining incorrect entries manually adjusted to ensure full correctness. For each university matched to HERDS, we consider all publications in the Open Academic Graph in each year that have at least one co-author affiliated with that university.

We work with the field experts at the AI for Good Foundation to identify AI-related publications.[42] First, we identify a small set of "seed" journals and conference proceedings that explicitly include terms like "artificial intelligence" and "machine learning" in their title (e.g., *Journal of Machine Learning Research* and *Proceedings of the International Joint Conference on Artificial Intelligence*). Second, to identify potential additional AI-related journals and conference proceedings, we look at all other journals and proceedings that have published work by the authors of the papers in the seed journals and proceedings. We manually filter this broader set of journals and conference proceedings to the ones that focus predominantly on AI, leading to a final list of 355 journals and conference proceedings globally.

To make sure that our results are not driven by firms' exposure broader (non-AI) CS-skilled workers, we control for firms' ex-ante exposure, via their hiring networks, to CS-strong universities. In particular, we construct an analogous measure of computer science publications by start-

[42]Learn more about the AI for Good Foundation here.

ing with a set of seed journals and conference proceedings across different fields of computer science (those with the terms "compilers," "databases," "cryptography," "computation," "software," "programming," "informatics," "robotics," or "information security" in their titles) and then manually screen all other journals and conference proceedings that publish papers by the same authors. We exclude any journal or conference proceeding that we classify as AI-related, leaving a total of 796 non-AI computer science journals and conference proceedings.

After identifying the set of AI-related and CS-related journals and conference proceedings, we classify the focus area of each researcher r as either AI, computer science, or neither. If at least one third of all publications co-authored by r are in either AI or CS journals and conference proceedings, then r is considered a candidate researcher. If r is a candidate researcher *and* at least half of r's AI/CS publications are in specifically AI journals and proceedings, then r is marked as an AI researcher. If more than half of r's AI/CS publications are in non-AI computer science journals and proceedings, then r is considered a non-AI CS researcher. Finally, if more than two thirds of r's publications are outside of the set of identified AI and CS journals and proceedings, then r is classified as a researcher in other (unrelated) fields.

At the university level, we compute the percentage of researchers in each year who are classified as AI researchers and the percentage of researchers who are classified as CS researchers. Researchers in other unrelated fields are included in the denominators of both measures. To reduce noise, we assume that each researcher is employed at the respective university in a non-publishing year if that researcher is employed at that university in both the following and the preceding year. For example, if researcher r is identified as affiliated with university u in both 2005 and 2007 but has no publications in 2006, then r is still considered to be affiliated with university u in year 2006. We then classify whether each university is AI-strong. We define a university as being strong in AI if it satisfies one of the following two criteria in at least one year between 2005 and 2009: (i) the number of AI researchers is in the top 5% of the distribution across all universities in a given year; (ii) the number of AI researchers is in the top 10% of the distribution, and the share of AI researchers (the number of AI researchers divided by the number of other researchers in the OAGv2 data) is in the top 5% of the distribution across all universities in a given year. We use the second criterion because there are some smaller, tech-oriented colleges that could potentially have a large share of researchers in AI but do not necessarily have large departments. Our results are robust to using other cutoffs and earlier years.

We verify that the OAGv2 publication data provide a reliable measure of university research. In Figure 4, we plot the log number of (all) researchers in each university in the OAGv2 data against the log R&D expenditure in the HERDS data. We find a strong positive correlation of 0.83. Furthermore, the top universities we identify as AI-strong include top AI departments, such as

Carnegie Mellon University, UCLA, Stanford University, UIUC, New York University, and University of Maryland College Park, but are *not* strongly correlated with the overall highest-ranked universities based on the U.S. News & World Report. For example, only 50% (39%) of the top 20 (top 50) universities are AI-strong universities, and among AI-strong universities, only 25% (56%) are ranked in the top 20 (top 50) universities in the U.S. News & World Report.

To construct the second ingredient for our instrument—firm exposure to AI-strong universities via the ex-ante firm-university hiring networks—we use our Cognism resume data. In these data, we observe the granting institutions of all degrees that workers list on their resumes. We disambiguate university names and match them to HERDS data. We define an individual i as a graduate of university u if i's resume lists at least one degree (undergraduate or graduate) from university u. We define an individual i as a *fresh graduate* from university u in year t if i joined a firm in year t and graduated from university u in year t or year $t-1$. These data offer comprehensive coverage of universities; for example, in 2010 there 668 of the 716 universities in the HERDS dataset have at least one fresh graduate in our resume data. Since the firms' hiring patterns might be different for STEM versus non-STEM workers (e.g., if a firm has a hiring relationship with an economics department for economic policy talent and with a business school for management talent), we also consider the firm-university hiring networks based specifically on STEM workers, in case such networks are more relevant for hiring AI workers. We define STEM workers as employees who have at least one degree with a major in either engineering (e.g., electrical, chemical, mechanical), physical sciences (e.g., math, physics, chemistry, computer science, statistics), or biological sciences (e.g., biology, pharmacology).

We compare the coverage of our university graduates data with official statistics from universities and show that our resume data cover a sizable proportion of university graduates in the U.S. In particular, we aggregate the data to university-year level by calculating the total number of fresh graduates from each university in each year. We compare these numbers with the total numbers of all degrees (bachelors, masters, and PhDs) conferred by each university in each year, using the Integrated Postsecondary Education Data System (IPEDS) data, which contain the total enrollment and the number of degrees conferred each year for all post-secondary institutions in the U.S. As of 2012 (the latest year of the IPEDS data), our resume data cover, on average, 59% of all fresh graduates at each university. The number of fresh graduates in the resume data is also highly correlated with graduates in the cross-section of universities (correlation=0.73).

Finally, we use our Cognism resume data to measure the share of all fresh university graduates from each university who get AI-skilled jobs in each year between 2006 and 2018. These data allow us to validate our premise that ex-ante AI-strong universities are able to increase the supply of AI-skilled graduates following the increase in commercial applications in AI in the first half of the

2010s, discussed below.

Instrument Validation. We first validate several core assumptions underlying the intuition behind our instrument. Confirming our key argument, we show that the increase in AI-trained graduates during the 2010s was much more pronounced in AI-strong universities than in non-AI-strong universities. Figure 5 plots the share of fresh graduates that are AI-trained from AI-strong and non-AI-strong universities from 2006 to 2018. In 2006, there were few AI graduates across the board, with the share of AI graduates below 0.3% for both AI-strong and non-AI-strong universities. Even in 2012, the share of AI graduates remained below 0.5% in both groups of universities. From 2012 to 2018, however, the share of AI graduates tripled (to about 1.5%) in AI-strong universities, while the share of AI graduates remained under 0.5% in non-AI-strong universities.

We then examine whether firm-university hiring networks provide the necessary variation for our instrumental variable strategy. First, our instrument leverages the variation in exposure to AI-strong universities across firms. Therefore, it requires that firms do not hire uniformly from the same universities. Empirically, most firms in our data concentrate their hiring in a small number of universities. On average, a firm hires 18% of its fresh graduates from the single main university in its network, 44% from its five main universities, and 59% from its 10 main universities. By contrast, the largest university produces only 1.6% of all fresh graduates, the largest five universities produce 7.1% of all fresh graduates, and the largest 10 universities produce 12.9% of all fresh graduates. Firms also hire disproportionately from universities located in the same state as their headquarters: on average, firms hire 38% of all fresh graduates, 37% of STEM fresh graduates, and 42% of AI fresh graduates from universities located in the same state. Second, in order for the ex-ante firm-university network to predict ex-post hiring of AI-skilled labor, firm-university networks need to be persistent over time. In column 1 of Table 9, we regress the share of fresh graduates hired from each university after 2010 on the share of fresh graduates hired from each university before 2010. We find a strong positive relationship, suggesting that firm-university networks are correlated over time. In column 2, we use the share of all workers employed in a firm in 2010 who graduated from each university to predict the share of fresh graduates hired from that university after 2010, again finding a strong positive correlation. The persistence of firm-university hiring networks also manifests in AI hiring. Columns 3 and 4 show that the universities from which a firm hired before 2010 also strongly predict the universities from which the firm will hire its AI-skilled workers after 2010. Finally, in columns 5 and 6, we show that pre-2010 firm-university hiring networks based only on STEM workers also strongly predict the universities from which firms hire their AI workers after 2010.

Our instrument is defined as follows for each firm i:

$$IV_i = \sum_u s_{iu}^{2010} AIstrong_u,$$

where s_{iu}^{2010} is the share of STEM workers in firm i in 2010 who graduated from university u, and $AIstrong_u$ equals one if university u is identified as an AI-strong university based on pre-2010 publications. We use firm-university hiring networks based on STEM workers in the firm as of 2010, because the instrument based on this measure has a stronger first stage; however, the results are very similar when we construct firm-university hiring networks using all workers in the firm as of 2010. To reduce noise, for each firm's hiring network, we consider the 50 universities from which the firm has the most workers in 2010. To control for the effects of general computer science (and not specifically AI), we construct an analogous measure of firms' exposure to CS-strong universities: $\sum_u s_{iu}^{2010} CSstrong_u$, where the weights s_{iu}^{2010} are firms' 2010 STEM hiring shares, and $CSstrong_u$ is the average share of (non-AI) CS researchers (the number of CS researchers divided by the number of all other researchers) at university u between 2005 and 2009. To control for the effects of overall university ranking, we also construct a measure of firms' exposure to top-ranked: $\sum_u s_{iu}^{2010} Top10_u$, where $Top10_u$ equals one if university $u$is one of the top 10 universities ranked by U.S. News & World Report in 2010.[43]

Before proceeding, we examine an important identification concern regarding our instrument: if firms anticipated the surge in demand for AI, they might have started building their connections to AI-strong universities before 2010, making firm-university hiring networks in 2010 endogenous to firms' ability to hire AI-trained students ex-post. This is unlikely, given the lack of both commercial interest in AI by firms and training of AI-skilled graduates by universities (Figure 5) prior to 2010. Indeed, we are able to confirm empirically that firms connected to AI-strong universities did not increase their share of hired fresh graduates from those universities from 2005 to 2010. Specifically, in Table 10, we find no significant relationship between the change in the share of fresh graduates from AI-strong universities in the pre-period (from 2005 to 2010) and our instrument.

In Appendix Table 11, we further show that firms that are more exposed to AI-strong universities are not growing faster before 2010, which supports the exclusion restriction that the exposure to AI-strong universities only affects firm growth through firms' AI investments after 2010.

First Stage. Table 12 presents the first stage of the instrument, where we regress our key independent variable—firm-level changes in the share of AI-skilled workers from 2010 to 2018—on the instrument, which measures ex-ante firm-level exposure to the supply of AI-trained university graduates from AI-strong universities. We control for firm-specific ex-ante exposure to CS-strong

[43]The top 10 universities include: Harvard, Princeton, Yale, University of Pennsylvania, Columbia, MIT, Stanford, Caltech, University of Chicago, Duke.

universities and top 10 universities and industry fixed effects in all specifications. In column 2, we additionally control for our baseline controls measured as of 2010: (i) firm-level variables (log employment, cash/assets, log sales, R&D/Sales, and log markups), (ii) the characteristics of the commuting zones where the firms are located in 2010 (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers); and (c) the log industry-average wage. The inclusion of these controls helps to address the concern that firms' ex-ante exposure to AI-strong universities might be correlated with other firm characteristics that can drive AI adoption and firm growth. In column 3, we also control for firms' pre-period sales and employment growth between 2000 and 2008 to address unobservable firm characteristics that might simultaneously drive firms' growth trajectories and their hiring of AI workers. In column 4, we further add state fixed effects to control for local labor market characteristics that might drive both universities' ability to produce AI graduates and firm growth. The first stage F-statistics are well above the conventional level of 10 for all specifications.

Figure 4. Correlation Between the Number of University Researchers and University R&D Expenditures

This figure is a binned scatterplot of the log number of researchers in each university against the log R&D expenditure in each university in 2010. Each dot represents roughly the same number of universities, and the solid line is the fitted regression line. The number of researchers in each university is the number of authors from that university with at least one publication in the OAGv2 data. The R&D expenditure of each university is from the NSF's HERDS data.

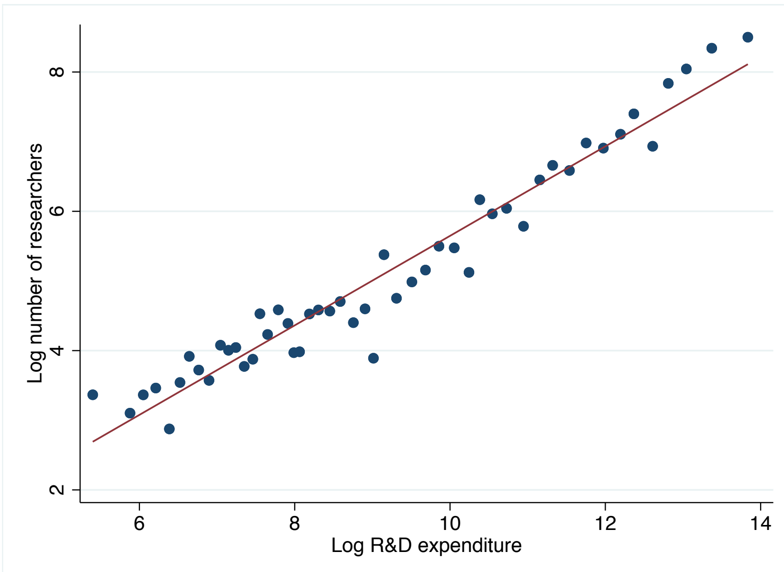


Figure 5. Time Series of the Share of AI-trained Fresh Graduates from Ex-ante AI-strong Universities and Other Universities

This figure plots the average share of AI-trained fresh graduates out of all fresh graduates from 2006 to 2018, separately for ex-ante AI-strong universities and non-AI-strong universities. We define a university as an AI-strong university if it satisfies one of the following two criteria in at least one year between 2005 and 2009: (i) the number of AI researchers is in the top 5% of the distribution across all universities in a given year; (ii) the number of AI researchers is in the top 10% of the distribution, and the share of AI researchers is in the top 5% of the distribution across all universities in a given year. We define an individual i as a fresh graduate from university u in year t if individual i joined a firm in year t and graduated from university u in year t or year $t-1$. An individual is considered an AI-trained fresh graduate in year t if the individual is a fresh graduate in year t and that individual's first job after graduation is an AI-skilled job. AI-skilled jobs are defined based on the methodology described in Section 3.2 and used throughout the paper.

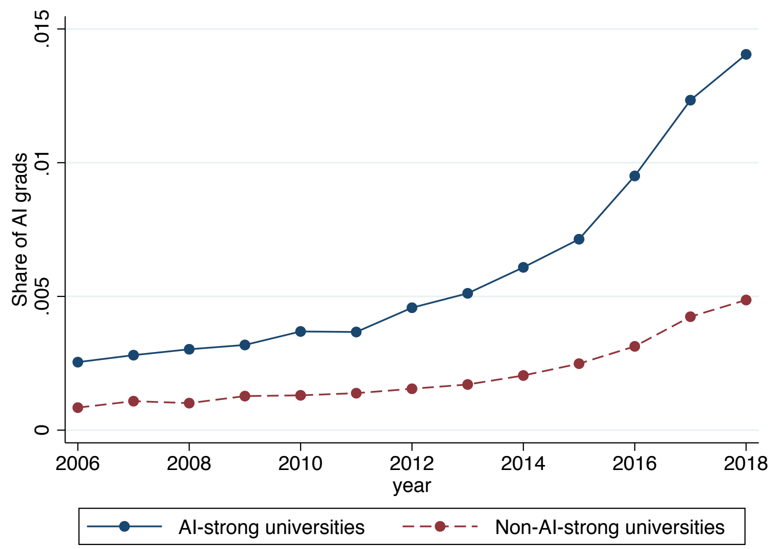


Table 9. Persistence of Firm-University Hiring Networks

This table reports the coefficients from regressing the share of each firm's fresh graduates hired from each university after 2010 on the pre-2010 firm-university network. Each observation is a firm-university pair. The dependent variable, constructed using the Cognism resume data, is the share of all fresh graduates hired from each university after 2010 in columns 1 and 2 and the share of AI-trained fresh graduates hired from each university after 2010 in columns 3–6. In columns 1 and 3, the independent variable is the share of all fresh graduates hired from each university between 2005 and 2010. We define an individual i as a fresh graduate from university u in year t if individual i joined a firm in year t and graduated from university u in year t or year $t-1$. In columns 2 and 4, the independent variable is the share of all workers in the firm in 2010 who graduated from each university. In column 5, the independent variable is the share of all STEM fresh graduates hired from each university before 2010. We define STEM workers as employees who have at least one degree with a major in either engineering (e.g., electrical, chemical, mechanical), physical sciences (e.g., math, physics, chemistry, computer science, statistics), or biological sciences (e.g., biology, pharmacology). In column 6, the independent variable is the share of STEM workers in the firm in 2010 who graduated from each university. All columns control for firm fixed effects and university fixed effects. Standard errors are clustered at the university level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Share of Post-2010 Hires		Share of Post-2010 AI Hires			
	(1)	(2)	(3)	(4)	(5)	(6)
Share of Pre-2010 Hires	0.465***		0.550***			
	(0.017)		(0.054)			
Share of 2010 Workers		0.147***		0.236***		
		(0.006)		(0.028)		
Share of Pre-2010 STEM Hires					0.342***	
					(0.040)	
Share of 2010 STEM Workers						0.197***
						(0.021)
Firm FE	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y
Observations	327,313	327,313	177,097	177,097	177,097	177,097

Table 10. Changes in Hiring from Ex-ante AI-strong Universities during the Pre-period (2005–2010)

This table reports the coefficients from regressing the change in the share of fresh graduates from AI-strong universities from 2005 to 2010 on the instrument (the share of STEM workers in the firm in 2010 who graduated from AI-strong universities). The independent variable is standardized to mean zero and standard deviation of one. Columns 2–5 control for ex-ante exposure to universities that are strong in CS research. Columns 3–5 also control for industry sector fixed effects. Columns 4 and 5 add the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Column 5 additionally controls for state fixed effects. Regressions are weighted by the number of Cognism resumes in 2010. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share of Fresh Graduates Hired from AI Hubs 2005-2010				
	(1)	(2)	(3)	(4)	(5)
Instrument	0.023	0.020	0.039	0.012	0.069
	(0.088)	(0.097)	(0.088)	(0.107)	(0.112)
CS Control	N	Y	Y	Y	Y
Industry FE	N	N	Y	Y	Y
Baseline Control	N	N	N	Y	Y
State FE	N	N	N	N	Y
Observations	830	830	829	829	825

Table 11. Firm Connections to AI-strong Universities and Firm Growth in the Pre-period

This table reports the coefficients from regressions of firm growth from 2000 to 2008 on the instrument – ex-ante firm-level exposure to AI-skilled graduates from AI-strong universities (see the definition of the instrument in Section 4.3 and the details of instrument construction in Appendix A). Regressions are weighted by the number of Cognism resumes in 2010. The dependent variables and the instrument are standardized to mean zero and standard deviation of one. We consider changes in log sales in columns 1 to 3, log employment in columns 4 to 6, and log market value in columns 7 to 9. All specifications control for industry sector fixed effects and ex-ante exposure to universities that are strong in computer science research as well as top 10 universities. Columns 2, 3 , 5, 6, 8, and 9 also control for the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Columns 3, 6, and 9 additionally control for state fixed effects. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales, 2000–2008			Δ Log Employment, 2000–2008			Δ Log Market Value, 2000–2008		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instrument	0.006	0.029	0.037	0.005	-0.003	0.002	-0.048	-0.022	-0.020
	(0.029)	(0.034)	(0.041)	(0.038)	(0.043)	(0.048)	(0.030)	(0.035)	(0.043)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Baseline Controls	N	Y	Y	N	Y	Y	N	Y	Y
State FE	N	N	Y	N	N	Y	N	N	Y
Observations	821	821	817	780	780	776	760	760	753

Table 12. First Stage of the Instrument

This table reports the first stage of the instrument, where we regress our key independent variable—firm-level changes in the share of AI-skilled workers from 2010 to 2018—on the instrument, which measures ex-ante firm-level exposure to the supply of AI-trained university graduates from AI-strong universities. The independent variable is the share of STEM workers in the firm in 2010 who graduate from ex-ante AI-strong research universities. The dependent variable is the resume-based measure of the growth in the share of AI workers from 2010 to 2018. Both the independent variable and the dependent variable are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects and ex-ante firm-level exposure to universities that are historically strong in CS research as well as top 10 universities. Columns 2–4 also include the baseline controls measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Columns 3 and 4 add controls for firm-level pre-trends: changes in log sales and log employment from 2000 to 2008. Column 4 adds state fixed effects. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. The first-stage F-statistics of the instrument are reported in both tables for all specifications. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share of AI Workers			
	(1)	(2)	(3)	(4)
Instrument	0.614***	0.400***	0.422***	0.458***
	(0.172)	(0.095)	(0.108)	(0.100)
Industry FE	Y	Y	Y	Y
CS Control	Y	Y	Y	Y
Baseline Controls	N	Y	Y	Y
Control Pre-trend	N	N	Y	Y
State FE	N	N	N	Y
F Statistic	12.8	17.7	15.4	21.0
Observations	1,001	1,001	777	773

Online Appendix

A1 Model of AI and Firm Growth

We outline a simple theoretical framework with heterogeneous multiple-product firms and both process and product innovation. The framework extends the models of industry dynamics in Bernard et al. (2010) and Melitz and Redding (2014). We aim to introduce the simplest model necessary to capture the essence of a broad class of models featuring product and process innovation and derive the empirical predictions that we can test using our data. They key feature of the model is that investments in AI can help firms grow either through product innovation (increasing the appeal of their existing or future products) or through process innovation (improving the productivity of their existing products).

Consider a continuum of products $i \in [0, 1]$, with the representative consumer's preferences taking the Constant Elasticity of Substitution (CES) form:

$$U = \left[\int_0^1 (a_i C_i)^{(\nu-1)/\nu} d_i \right]^{\nu/(\nu-1)}, \quad \nu > 1,$$

where C_i is consumption of product i, and a_i captures the relative importance of product i.

For each product i, there is a set of horizontally differentiated varieties, produced by different firms. Preferences across these varieties for any product also take the CES form:

$$C_i = \left[\int_{f \in F_i} (\lambda_{i,f} c_{i,f})^{(\sigma-1)\sigma} df \right]^{\sigma/(\sigma-1)}, \quad \sigma > 1,$$

where f indexes firm varieties within products, and F_i is the set of all firms that produce varieties of product i. The demand parameter $\lambda_{i,f}$ determines the relative demand for firm f variety of the product. For brevity, we assume that the elasticity of substitution across varieties of a product is the same for all products. We also assume that elasticity of substitution across varieties within products is greater than the elasticity of substitution across products (i.e., $\sigma > \nu$), since consumers are likely to first form demand for a specific product and then search for varieties within that product.

When a firm enters, it draws its initial productivity in each product, $\varphi_{i,f} \in [\underline{\varphi}, \overline{\varphi}]$, and consumer tastes for the characteristics of its product variety in each product, $\lambda_{i,f} \in [\underline{\lambda}, \overline{\lambda}]$. While $\varphi_{i,f}$ captures the firm's production efficiency, $\lambda_{i,f}$ determines the product appeal (for example, a firm with a higher-quality product has a higher $\lambda_{i,f}$). Both productivity $\varphi_{i,f}$ and consumer tastes $\lambda_{i,f}$ are firm-

product-specific and differ across various products produced by the firm.[44]

The production technology takes the following form. A firm incurs fixed corporate headquarters costs of M_h units of labor, which is irrespective of the number of products produced, and a fixed cost of M_i units of labor for each product i that it produces. Both fixed costs are homogeneous across firms. Labor has unit cost w. Within each product i, each firm supplies a distinct horizontally-differentiated variety. There is a constant marginal cost of producing a variety, which is inversely proportional to firm productivity $\varphi_{i,f}$. The total amount of labor required to produce $q_{i,f}$ units of a variety i is therefore:

$$l_{i,f} = M_i + \frac{q_{i,f}}{\varphi_{i,f}}.$$

Because of monopolistic competition, each firm chooses its price to maximize its profits subject to a downward-sloping residual demand curve with constant elasticity σ. The equilibrium price for each variety is a constant mark-up over marginal cost:

$$p_{i,f}(\varphi_{i,f}, \lambda_{i,f}) = \frac{\sigma}{\sigma - 1} \frac{w}{\varphi_{i,f}}.$$

Firm profits for product i are therefore:

$$\pi_{i,f}(\varphi_{i,f}, \lambda_{i,f}) = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} R_i \left(\frac{\varphi_{i,f} \lambda_{i,f} P_i}{w} \right)^{\sigma-1} - wM_i,$$

where $P_i = \left[\int_{f \in F_i} (\frac{p_{i,f}(\omega)}{\lambda_{i,f}(\omega)})^{1-\sigma} df \right]^{1/(1-\sigma)}$ is the price index for product i, and R_i is an index of market demand that proportionally scales every firm's residual demand and does not vary across firms within a product. With a continuum of firms, each firm is of measure zero relative to the market as a whole, and correspondingly its production in any product has measure zero relative to all firms producing that product.

A firm observes its productivity and consumer tastes before deciding whether to produce each product. Firm f produces product i if and only if $\pi_{i,f}(\varphi_{i,f}, \lambda_{i,f}) > 0$. Profits are increasing in productivity $\varphi_{i,f}$ and product appeal $\lambda_{i,f}$, therefore firms with higher productivity and product appeal for a product are more likely to actively produce the product. Suppose Φ_f is the set of products with positive profits for a firm, then the firm's total profit is:

$$\pi_f = \int_{i \in \Phi_f} \pi_{i,f}(\varphi_{i,f}, \lambda_{i,f}) di - wM_h.$$

Process Innovation and Productivity Improvements. When a firm invests in artificial intelli-

[44] Bernard et al. (2010) assume that productivity is common across products within firms, but we relax this assumption.

gence technologies, it may lead to process innovation and higher production efficiency. We introduce process innovation in the model similarly to Bustos (2011). A firm with productivity $\varphi_{i,f}$ can pay additional fixed costs to increase the productivity of all products that it is actively producing to $\iota\varphi_{i,f}$, where $\iota > 1$ is the proportional productivity increase. The technology adoption choice involves a tradeoff between a fixed cost and a per-unit profit increase. For each product the firm produces, costs decrease proportionately, which increases the firm's profits from that product. Importantly, process innovation does not change the productivity of products that the firm does not actively produce and therefore does not change the set of products Φ_f.

Product Innovation. Investments in artificial intelligence technologies may also affect product innovation. Suppose that a firm can conduct product innovation to produce products with higher than existing consumer tastes (or product appeal). More specifically, by investing $\psi_f x^2$ units of labor, $x \in [0,1]$ fraction of all the products are randomly drawn, which may include products that the firm already produces and products that the firm is not actively producing. For these randomly drawn products, the firm's existing consumer tastes $\lambda_{i,f}$ are multiplied by $\kappa > 1$. Product innovation can increase firms' revenue in two ways: first, it may increase the product appeal and revenue of existing products; second, by increasing the product appeal of products which are unprofitable for the firms to produce originally, it may also expand Φ_f, the set of products that the firm produces with positive profits.

Artificial intelligence can potentially reduce the cost of product innovation ψ_f and spur firm growth, as discussed in Section 1. First, the ability of AI to analyze large datasets and make predictions can reduce the cost of experimentation, which is key to product development. Second, firms can improve the quality of products and services by building AI models directly into products. Third, AI can reduce the costs of product customization by learning more efficiently about customers' tastes and needs from big data, which help improve product appeal to customers.

The two channels—productivity improvements and product innovation—both lead to higher firm growth in revenue but have very different predictions. Process innovation leads to lower costs and higher productivity, while the effects of product innovation on the firm's total costs and productivity are ambiguous. On the other hand, product innovation leads to the creation of new products and improvements of existing products, while process innovation does not affect the scope of products firms produce.

A2 Case Studies on Firms' AI Investments

In order to illustrate the wide range of applications of AI technologies by individual firms, we

provide detailed summaries of the investment patterns and uses of AI technologies within four firms in four different industries.

A2.1 UnitedHealth Group

UnitedHealth Group (UNH) is a large managed healthcare company based in Minnetonka, Minnesota. The group includes a healthcare arm (UnitedHealthcare) established in 1977 and a new technology arm founded in 2011 (Optum). While the UnitedHealthcare arm makes use of AI techniques to optimize operations ranging from cost projections to fraud detection in medical claims, the launch of Optum highlights the way in which firms such as UNH can leverage AI technologies to expand operations by creating new products and entering new market segments. UNH is one of very few companies with access to detailed patient, patient-physician, and drug-patient interaction data for large portions of the U.S. and many additional global locations, making it perfectly placed to harness AI in its operations.

AI use cases and product impact. Most of the AI investments and impact at UNH center around its Optum arm. The traditional UnitedHealthcare part of UNH uses AI in a limited capacity for predictive analytics that inform business decisions and safeguards for vulnerabilities such as fraud detection. The launch of Optum in 2011 has enabled UNH to leverage AI technologies to deliver new products across several healthcare markets. At its core, Optum is a vast data store of proprietary and 3rd party datasets linked together to enable machine-learning-based analysis. Specifically, the AI-powered Optum products include: (i) statistics on drugs and potential alternatives through the pharmaceutical platform Optum Rx; (ii) analysis of electronic medical records through the Optum One platform for physicians; and (iii) the Optum Population Health Management platform for larger institutions (including employers and federal and state agencies) to optimize costs and accessibility to care. The AI-powered OptumIQ system, which is leveraged throughout the Optum solutions, also targets machine-learning-based prediction and diagnostics for diseases such as atrial fibrillation.

Timeline of AI investments at UNH. The use of AI technologies at UNH traces further back than at most firms. As early as the 1990s, UNH piloted AdjudiPro, an AI-powered platform for processing claims from physicians. However, the presence of AI-skilled labor at UNH remained low throughout the 1990s and 2000s, noticeably picking up in 2011 with the launch of the Optum platform. Thereafter, UNH's investment in AI human capital rose steadily throughout the 2010s. The Optum arm of the firm released the Optum360 and Impact Pro products in 2013 and the Optum One Analytics Platform in 2014, prompting a further acceleration in the rise of UNH's AI human capital in the second half of the decade. The timeline of AI investments at UNH is displayed in Figure A1.

Internal structure of UNH's AI workforce. UNH has a centralized approach to AI integration,

with strategic decisions primarily coming from the headquarters in Minnesota and regional offices handling specific applications. Correspondingly, the majority of UNH's AI workforce concentrates in Minneapolis and Minnetonka, including senior personnel heading AI and machine learning efforts, automation/deployment, consumer analytics, and Optum enterprise analytics. Locations outside of the headquarters tend to employ predominantly engineering and general IT personnel to support the AI efforts.

A2.2 JPMorgan Chase & Co

JPMorgan Chase & Co (JPM) is the largest bank in the U.S., based in New York City, NY, with consumer banking that has relationships with more than half of U.S. households, a commercial banking arm, a large investment banking business, and a sizable asset management arm. The bank stores hundreds of petabytes of data ranging from credit card transactions and loan applications, to financial news and market data, to alternative data sources.

AI use cases and product impact. The main use cases for AI at JPM fall into the following categories: (i) risk modeling and management ranging from internal cybersecurity to fraud detection in consumer banking and assessment of geo-political risks; (ii) quantitative analysis and algorithmic investment products, including the Algo Central, LOXM, and DeepX programs aimed at executing trades at both maximal speed and optimal prices; (iii) general analytics for Big Data use in broad internal applications including recruiting; and (iv) product development, including enhancements to mobile apps and customer support through AI-powered virtual assistants. In addition, JPM also employs AI in more peripheral applications, for example, with methods for processing of alternative data such as satellite images and mapping contingency plans for AI-driven workforce disruptions. The use of AI at JPM is aimed at both cutting costs (e.g., through risk assessment) and creating new products (e.g., machine-learning-powered trading platforms such as DeepX).

Timeline of AI investments at JPM. As highlighted by Figure A2, investments in AI at JPM began at the turn of the century, with a steady increase through the first decade turning into an exponential growth in the second decade. The explosion in AI investments at JPM during the 2010s is marked by the acquisition of the multimedia recommendations patent in 2011; an underscoring of the risks associated with data security following a data leak in 2016; and finally the establishment of a dedicated AI research initiative (Machine Learning Center for Excellence) spearheaded by Dr. Manuela Veloso (previously the Chair of the Machine Learning Department at Carnegie Mellon University) in 2018.

Internal structure of JP Morgan's AI workforce. AI efforts at JPM are centered in the New York location, with peripheral AI expertise throughout the U.S., in London, and in India. JPM has taken a top-down approach to AI investments, with involvement from the highest levels of management

and the establishment of a dedicated AI research team in 2018. At the same time, JPM's investments in AI have seen not only the formation of dedicated AI hubs, but also a different approach to corporate structuring. Specifically, the firm's approach relies heavily on small skilled and responsive AI "task-forces" specializing in different sectors (quantitative analysis, user experience, etc.), which can alternatively work on experimental projects (e.g., satellite imagery analysis) or coordinate together to work on core applications (trading algorithms, firm-wide cybersecurity).

A2.3 Caterpillar Inc.

Caterpillar Inc. is a large construction manufacturing firm headquartered in Deerfield, IL, with a variety of additional business activities including financial products and insurance. The firm has correspondingly varied applications for AI, ranging from inventory management to part recognition, to credit scoring for machinery financing.

AI use cases and product impact. AI investments at Caterpillar are organized along several key verticals. First, the Data Innovation Lab at UIUC conducts core projects in demand forecasting (unstable demand anticipation) and inventory management, in part identification (using techniques from image recognition), and in tracking and tracing technology for fleet management. Second, Caterpillar's asset intelligence efforts include a product line of Internet of Things (IoT) style analytics for managers and machine operators, which facilitates data collection, interpretation, predictive maintenance, and integration. Lastly, smaller targeted efforts at Caterpillar also employ AI techniques in other parts of the business, including leveraging sensor-based data for equipment management and using drone data to optimize job site organization. Caterpillar's uses of AI serve to modernize the firm's machinery, streamline operations and reduce waste through better forecasting and inventory management, and expand the product offerings with the IoT product line and efficient long-term service contracts.

Timeline of AI investments at Caterpillar. Caterpillar began employing workers with AI expertise at the turn of the century, but the growth in the firm's AI workforce went hand-in-hand with the growth in the firm's overall workforce throughout the 2000s (with a dip during the financial crisis). The share of AI employees at Caterpillar noticeably picked up only in mid-2010s, with the CEO Douglas Obenhelmer underscoring the importance of capitalizing on the firm's vast available data resources. Since 2014, Caterpillar has aggressively pursued the development of "smart" machinery, connecting it to predictive IoT-style networks and developing better models for demand prediction. In 2015, Caterpillar established the Analytics and Innovation Division headed by Greg Foley, and in 2016, the firm hired Morgan Vawters as the Chief of Analytics. The timeline of Caterpillar's investments in AI human capital is presented in Figure A3.

Internal structure of Caterpillar's AI workforce. The majority of the AI employees at Caterpillar are in the firm's Technology division, with notable presence also in Business and Production

departments. The major locations setting the trend for Caterpillar's AI adoption are the company centers in Chicago and Peoria, Illinois, with projects percolating through the dedicated research centers such as the Champaign Innovation Center and production centers such as the manufacturing plant in Aurora, Illinois.

A2.4 Qualcomm Inc.

Qualcomm Inc. is a wireless telecommunications firm headquartered in San Diego, CA. The firm produces a number of products including semiconductors, hardware, software, and other services related to wireless technology. Device manufacturers such as Apple are Qualcomm's primary clients.

AI use cases and product impact. The principal use of AI at Qualcomm over the past decade and a half has been the improvement of its core products. This includes optimization of chips within mobile devices, improvements to the camera using techniques from computer vision for face recognition and auto-adjustments, audio and video processing, physical sensitivity, power use, and location tracking capabilities. More recently, Qualcomm made a large investment in the development of the Snapdragon Neural Processing Engine (SNPE) platform, which offers a combination of hardware and software on android devices that allows developers to more easily create AI-powered or assisted applications. With the exception of a few stand-alone projects for internal data processing efficiency (e.g., improving internal servers), Qualcomm does not appear to be heavily invested in applying AI for applications such as sales or supply chain optimization, unlike Caterpillar Inc. described above.

Outside of its core businesses, Qualcomm has invested in a number of side products at more exploratory or proof-of-concept stages, such as general work on autonomous vehicles, or enterprise partnerships, for example with Accenture and Kellogg on virtual reality tracking of customers for marketing purposes. This highlights the broad scope of AI technologies that facilitate firms entering new markets: for example, the autonomous vehicle work at Qualcomm makes use of the efforts aimed at enhancing smartphone components, only applied to a different domain.

Timeline of AI investments at Qualcomm. As can be seen from the timeline in Figure A4, the presence of AI employees at Qualcomm began earlier than in the other firms, and by 2007 the firm initiated dedicated AI research projects in its research arm. The ramp up continued through 2013, marked by collaborations with outside partners such as Brain Corp and internal projects on problems such as face detection. After 2013, Qualcomm saw notable consequences of the earlier investments, including the first release of SNPE and the formation of an organizationally separate AI research group, but the share of Qualcomm's overall workforce that is skilled in AI remained approximately flat from 2013 to 2018.

Internal structure of Qualcomm's AI workforce. Between 2000 and 2018, the majority of Qual-

comm's AI employees have been engineers focused on the improvement of the core product being developed at each point in time, supported by an auxiliary staff of patent counsels and data scientists. In 2018, Qualcomm established a separate AI research group, which is bringing about increased centralization of its AI workforce. Specifically, AI efforts at Qualcomm are organized around the San Diego headquarters, with leadership on overall AI strategy, the newly formed AI research group, and teams spanning nearly every project from computer vision R&D to GPU architecture. Smaller AI offices, scattered mostly throughout the U.S. and Canada, tend to focus on single elements of Qualcomm's AI initiative (for example, SNPE in Toronto and positioning sensors in Santa Clara).

Figure A1. Timeline of AI investments by UnitedHealth Group

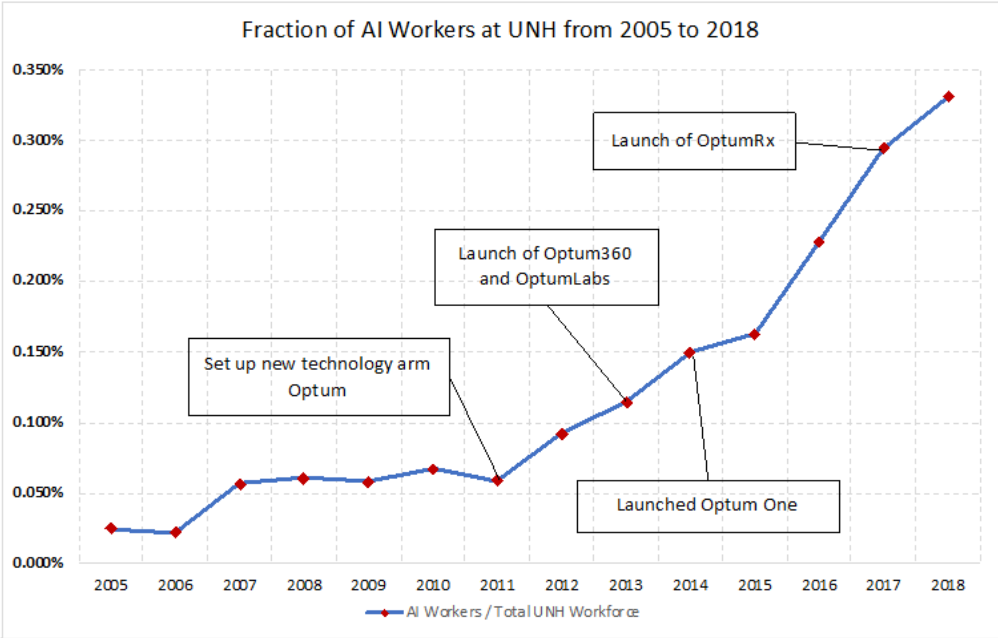


Figure A2. Timeline of AI investments by JPMorgan Chase & Co

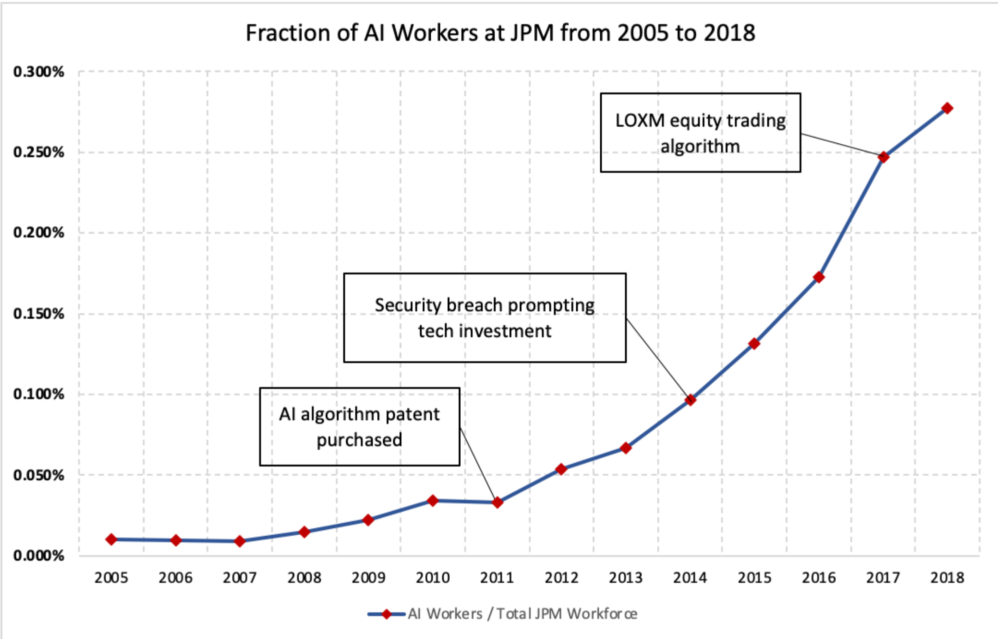


Figure A3. Timeline of AI investments by Caterpillar Inc

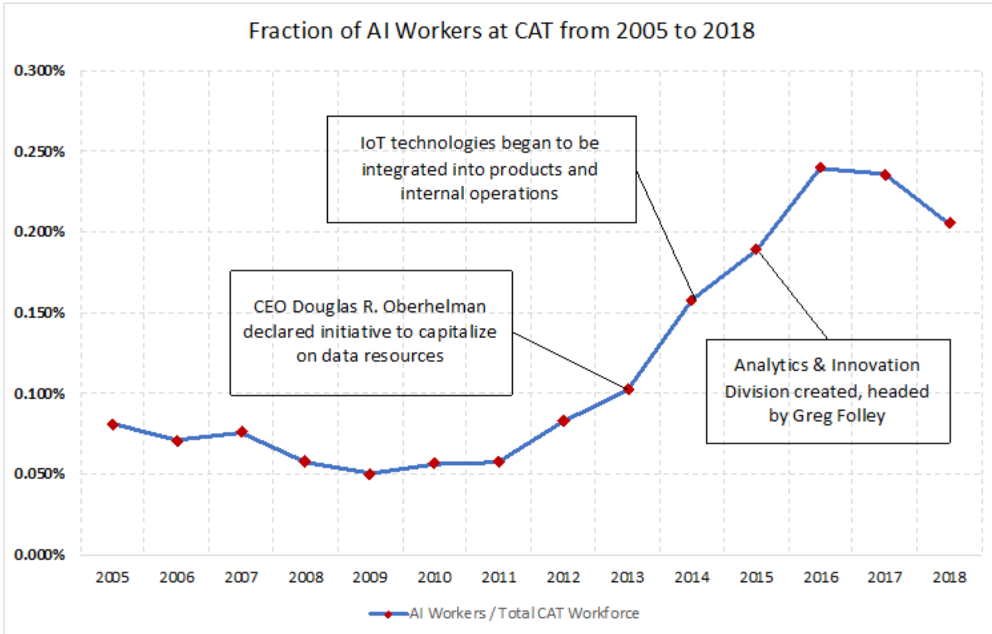
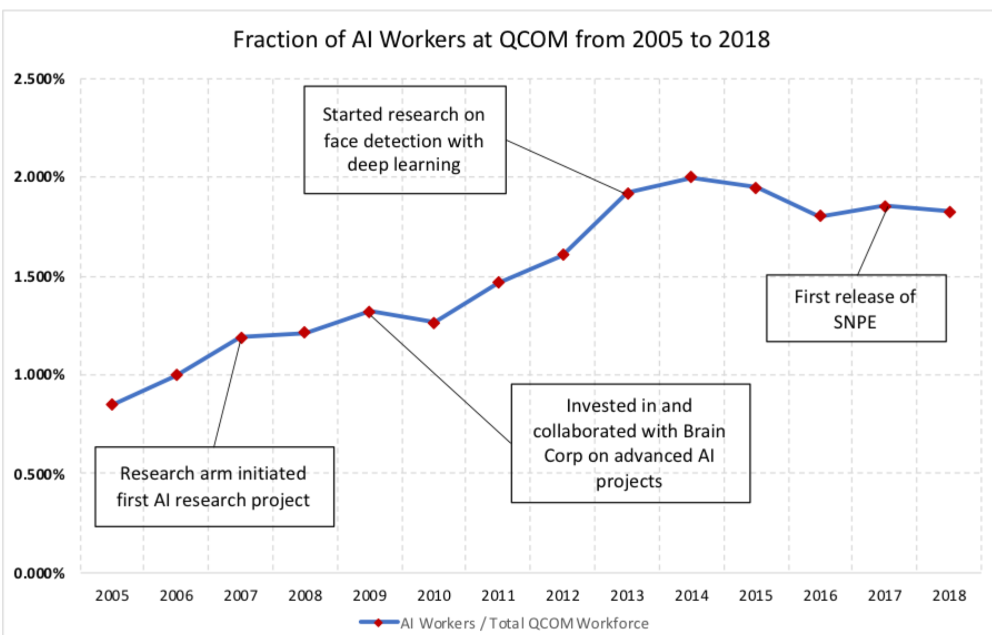


Figure A4. Timeline of AI investments by Qualcomm Inc



A3 Additional Figures and Tables

Figure A1. Matching Rate to Compustat in Job Postings Data

This figure shows the time series of the share of all job postings and the share of AI job postings (job postings with continuous measure ω_j^{AI} above 0.1) that are matched to Compustat firms in the Burning Glass data in 2007 and in each year from 2010 to 2018.

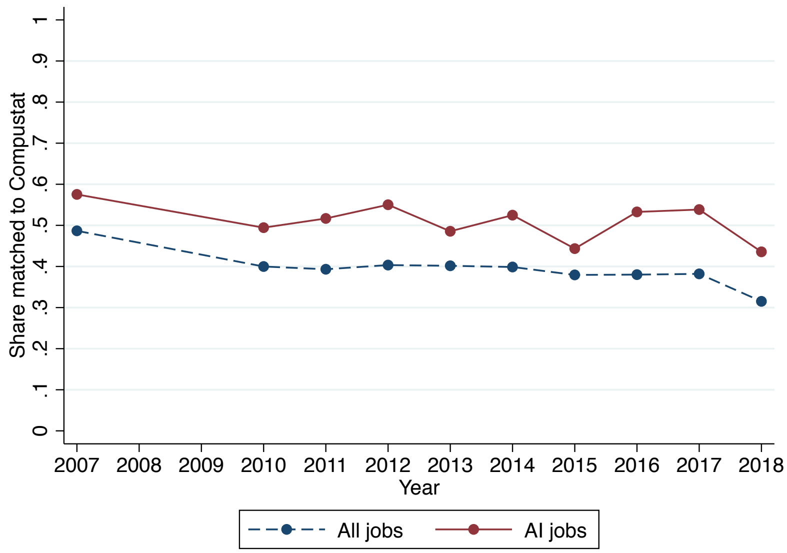


Figure A2. Distribution of AI Investments across U.S. Geographies

This figure shows a heat map of changes in the job-posting-based measure of AI investments across geographies in the U.S. The figure plots the change in the average AI-relatedness measure (w_j^{AI}) of job postings of public firms in each commuting zone from 2010 to 2018.

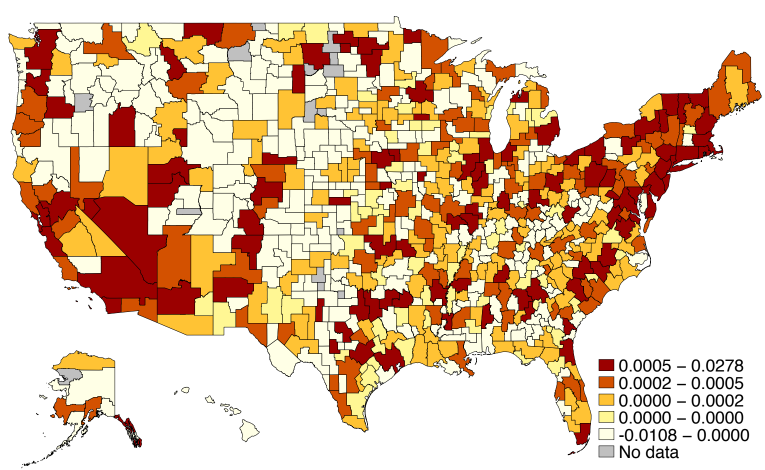
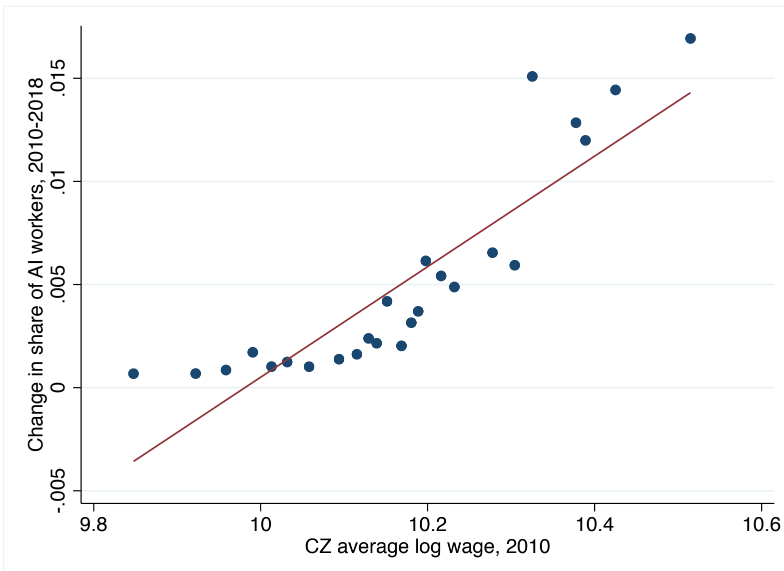
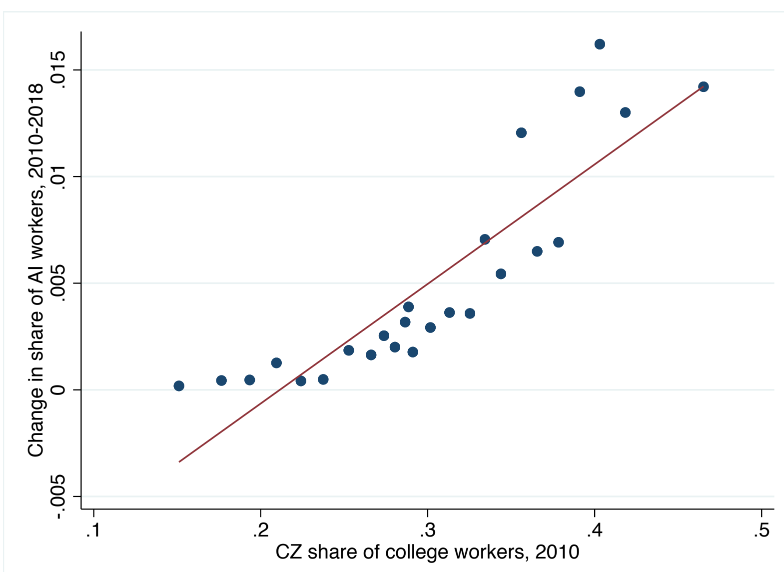


Figure A3. AI Investments and Local Conditions

This figure presents binned scatterplots of commuting-zone-level AI investments against local conditions. Solid lines are the fitted regression lines, where the regressions are weighted by commuting zones' populations in 2010. The y-axis is the change in AI investments (i.e., the change in the share of AI workers) from 2010 to 2018, using the Burning Glass data (based on the sample of public firms). The x-axis in Panel (a) is the average log wage of a commuting zone in 2010. The x-axis in Panel (b) is the share of college educated workers in a commuting zone in 2010. The log wage and the share of college-educated workers are from the Census American Community Survey. The t-statistic on the regression slope is 23.8 in Panel (a) and 24.1 in Panel (b).



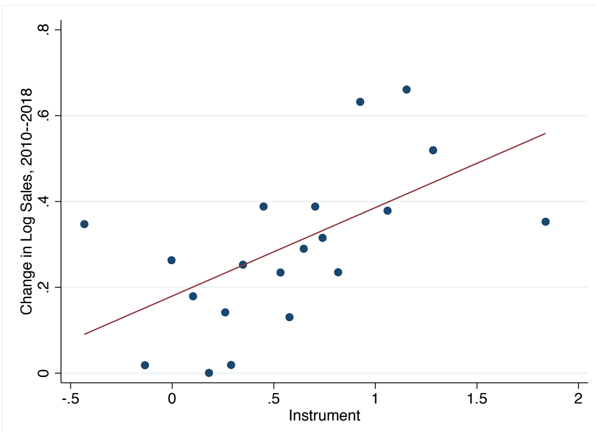
(a) AI Investments and Local Average Wage



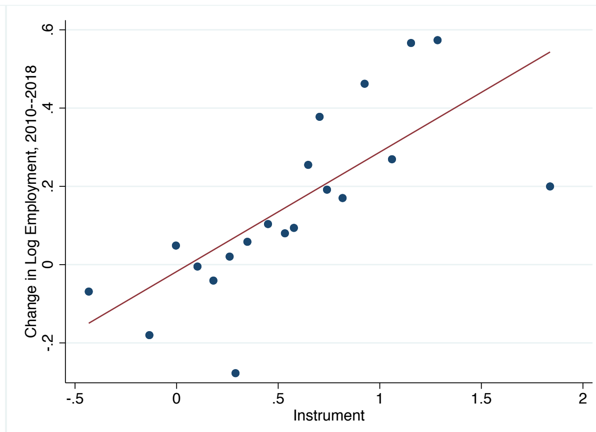
(b) AI Investments and Local Share of College-educated Workers

Figure A4. Relationship between the Instrument and Firm Growth

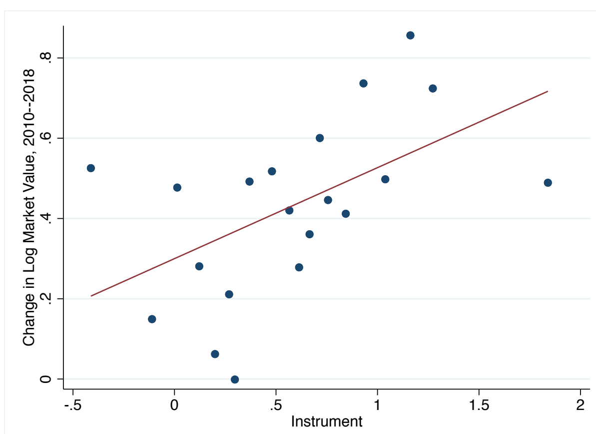
This figure presents binned scatterplots of firm growth from 2010 to 2018 against the instrument – ex-ante firm-level exposure to AI-skilled graduates from AI-strong universities (see the definition of the instrument in Section 4.3 and the details of instrument construction in Appendix A). Solid lines are the fitted regression lines. For firm growth, we consider changes in log sales in Panel (a), log employment in Panel (b), and log market value in Panel (c). The observations are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects, state fixed effects, baseline controls measured as of 2010 (firm-level log sales, cash/assets, R&D/sales, log markup, and log number of resumes; log industry wage; characteristics of the commuting zones where the firms are located), as well as firm-level changes in log sales and log employment from 2000 to 2008.



(a) Sales



(b) Employment



(c) Market Value

Table A1. Skills with Highest AI-Relatedness Measures in Burning Glass Job Postings

This table lists the top skills in the Burning Glass data ranked by the skill-level AI measure w_s^{AI}. For each skill, we report the percentage of jobs requiring that skill that also require one of the four core AI skills—artificial intelligence, machine learning, computer vision, and natural language processing. For example, for jobs that require "Recurrent Neural Network (RNN)," 96.5% also require one of the four core AI-skills. Only skills that appear in least 50 job postings are included.

#	Skills	AI-relatedness Score
1	Artificial Intelligence	1.000
2	Computer Vision	1.000
3	Machine Learning	1.000
4	Natural Language Processing	1.000
5	ND4J (software)	0.980
6	Kernel Methods	0.979
7	Microsoft Cognitive Toolkit	0.975
8	Xgboost	0.972
9	Sentiment Classification	0.971
10	Long Short-Term Memory (LSTM)	0.971
11	Libsvm	0.968
12	Semi-Supervised Learning	0.968
13	Recurrent Neural Network (RNN)	0.965
14	Word2Vec	0.956
15	MXNet	0.953
16	Caffe Deep Learning Framework	0.950
17	Autoencoders	0.949
18	MLPACK (C++ library)	0.942
19	Keras	0.941
20	Theano	0.938
21	Torch (Machine Learning)	0.932
22	Wabbit	0.929
23	Boosting (Machine Learning)	0.905
24	TensorFlow	0.904
25	Vowpal	0.903
26	Convolutional Neural Network (CNN)	0.897
27	Jung Framework	0.894
28	OpenNLP	0.894
29	Natural Language Toolkit (NLTK)	0.892
30	Unsupervised Learning	0.891
31	Dlib	0.891
32	Scikit-learn	0.889
33	Latent Semantic Analysis	0.889
34	Latent Dirichlet Allocation	0.889
35	Stochastic Gradient Descent (SGD)	0.881
36	Gradient boosting	0.872
37	Dimensionality Reduction	0.861
38	Deep Learning	0.859
39	DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	0.855
40	AI ChatBot	0.844
41	Recommender Systems	0.842
42	Random Forests	0.840
43	Deeplearning4j	0.839
44	Support Vector Machines (SVM)	0.817
45	Unstructured Information Management Architecture	0.806
46	Apache UIMA	0.805
47	Maximum Entropy Classifier	0.799
48	Hidden Markov Model (HMM)	0.796
49	Pybrain	0.786
50	Computational Linguistics	0.780
51	Naive Bayes	0.768
52	H2O (software)	0.763
53	Expectation-Maximization (EM) Algorithm	0.763
54	WEKA	0.761
55	Clustering Algorithms	0.740
56	Matrix Factorization	0.739
57	Object Recognition	0.727
58	Classification Algorithms	0.721
59	Information Extraction	0.709
60	Image Recognition	0.706
61	Bayesian Networks	0.705
62	Supervised Learning (Machine Learning)	0.695
63	OpenCV	0.688
64	K-Means	0.683
65	Sentiment Analysis / Opinion Mining	0.679
66	Machine Translation (MT)	0.655
67	Neural Networks	0.640

Table A2. Examples of AI and Non-AI Job Postings in Burning Glass

This table displays examples of job postings and their continuous AI measure ω_j^{AI}. Jobs 1–10 are examples of AI-skilled jobs, with the first five being non-data-specific and the last 5 being data-specific. Jobs 11–20 are examples of non-AI-skilled jobs, with the first five being data specific and the last 5 being non-data-specific. The AI relatedness score of each skill is listed in parentheses.

	Job Title	Employer	Skills	Score
	AI jobs			
1	Research Engineer - Natural Language Processing	InterActiveCorp	Machine Learning (1), Natural Language Processing (1), Natural Language Toolkit (0.895), Computational Linguistics (0.777), WEKA (0.760), Information Extraction (0.709), Mahout (0.593), Information Retrieval (0.360), Apache Hadoop (0.204), Lucene (0.188), SOLR (0.142), C++ (0.067), Software Engineering (0.043), Python (0.116), Lexical Semantics (0.625), Ontologies (0.326), Java (0.040), PERL Scripting Language (0.034), Relational Databases (0.024), SQL (0.023), Search Analytics (0.022), Shell Scripting (0.020), Web Analytics (0.012), Research (0.011), Online Research (0.010), Extensible Markup Language (0.010)	0.31
2	Computer Vision & Image Processing Researcher	Rambus Incorporated	Computer Vision (1), Object Recognition (0.725), OpenCV (0.689), Pattern Recognition (0.442), CUDA (0.362), Image Processing (0.179), Troubleshooting Technical Issues (0.006), C++ (0.067), Communication Skills (0.003), MATLAB (0.113), Self-Motivation (0.002), Optical System Design and Analysis (0.019), Research (0.011), Writing (0.004), OpenGL (0.117), Prototyping (0.042), Very Large Scale Integration (0.037), Creativity (0.007)	0.21
3	Algorithm Developer	IBM	Natural Language Processing (1), Machine Learning (1), IBM Watson (0.125), Java (0.040), Software Development (0.027), Candidate Generation (0.013), Creativity (0.007), Troubleshooting (0.003), English (0.002)	0.25
4	Senior Autonomous Vehicle Localization Software Engineer	Nvidia Corporation	Computer Vision (1), Deep Learning (0.859), Linear Algebra (0.187), OpenGL (0.117), C++ (0.067), Software Engineering (0.043), Geometry (0.009), Motor Vehicle Operation (0.006), Teamwork / Collaboration (0.005), Calibration (0.004)	0.230
5	Speech Recognition Scientist	Vocera Communications	Computational Linguistics (0.780), Automatic Speech Recognition (0.457), Speech Recognition (0.215), Experiments (0.045), Performance tuning (0.011), Research (0.011), Written Communication (0.003)	0.217
6	Data Scientist	Zappos	Machine Learning (1), Natural Language Processing (1), Boosting (Machine Learning) (0.902), Support Vector Machines (0.816), Naive Bayes (0.759), Matrix Factorization (0.738), Classification Algorithms (0.718), Data Science (0.379), Data Mining (0.159), NoSQL (0.119), Clustering (0.103), Data Structures (0.069), Relational DataBase Management System (0.028), SQL (0.023), Attribution Modeling (0.072), Detail-Oriented (0.002), Revenue Projections (0.003), Traffic Maintenance (0.002)	0.384
7	Data Mining Engineer	Apple Inc.	Artificial Intelligence (1), Natural Language Processing (1), Machine Learning (1), Unsupervised Learning (0.891), Supervised Learning (0.696), Mahout (0.593), Pattern Recognition (0.442), Apache Hadoop (0.204), Image Processing (0.179), Data Mining (0.159), NoSQL (0.119), Data Collection (0.008), Communication Skills (0.003), Java (0.040), Detail-Oriented (0.002), MATLAB (0.113), SQL (0.023), Network Engineering (0.007), Research (0.011), Python (0.116), Meeting Deadlines (0.002), R (0.248), Predictive Models (0.243)	0..309
8	Big Data Engineer	Socialwire	Machine Learning (1), Recommender Systems (0.843), MapReduce (0.285), Apache Hadoop (0.204), Big Data (0.196), Facebook (0.006), R (0.248), Pinterest (0.003), Writing (0.004), MATLAB (0.113)	0.290
9	Big Data Senior Data Scientist	AT&T	Machine Learning (1), WEKA (0.760), Clustering Algorithms (0.738), Mahout (0.593), Data Science (0.379), Big Data (0.196), Data Mining (0.159), Clustering (0.103), Simulation (0.028), Experimental Testing (0.039), R (0.248), SPSS (0.067), Creativity (0.007), SAS (0.053), Information Systems (0.007), Experiments (0.045), Presentation Skills (0.006), Research (0.011), Data Quality (0.025)	0.235
10	Data Scientist	Warby Parker	Natural Language Processing (1), Natural Language Toolkit (0.895), Random Forests (0.839), Pandas (0.498), Data Science (0.379), PIG (0.290), Apache Hadoop (0.204), Data Mining (0.159), Data Visualization (0.136), Tableau (0.074), Pentaho (0.058), NumPy (0.552), SQL (0.023), Python (0.116), Java (0.040), DevOps (0.039), Agile Development (0.030), Creativity (0.007), Django (0.039), Apache Webserver (0.034), Predictive Models (0.243), Relational Databases (0.024), Data Modeling (0.037)	0.249
	Non-AI jobs			
11	Director Of Business Intelligence	Odesus Incorporated	Data Science (0.379), Data Transformation (0.060), SQL (0.023), Communication Skills (0.003), SQL Server Reporting Services (0.009), SQL Server (0.009), SQL Server Analysis Services (0.034), Budgeting (0.001), Microsoft Sharepoint (0.002), Data Warehousing (0.025), MySQL (0.028), Key Performance Indicators (0.006), Problem Solving (0.005), Web Analytics (0.012), Market Research (0.006), Data Modeling (0.037), Business Intelligence (0.026), Creativity (0.007)	0.037
12	Director, Data & Analytics	Decision Resources	Big Data (0.196), Business Intelligence (0.026), Business Intelligence Industry Knowledge (0.020), Teamwork / Collaboration (0.005), Biopharmaceutical Industry Knowledge (0.004), Communication Skills (0.003)	0.042
13	Senior Healthcare Economics Data Analyst	UnitedHealth Group	Tableau (0.076), Advanced Statistics (0.149), SAS (0.053), Data Analysis (0.026), SQL (0.023), Economics (0.016), Database Design (0.014), Clinical Data Analysis (0.012), Clinical Data Review (0.010), Business Process (0.006)	0.039
14	Data Analyst	United Technologies Corporation	Data Analysis (0.026), Data Quality (0.025), Data Management (0.018), Database Design (0.014), Proposal Writing (0.007), Product Improvement (0.007), Business Planning (0.002)	0.014
15	Sas Database Administrator	Pitney Bowes	SAS (0.053), SQL (0.023), Business Strategy (0.009), Teradata DBA (0.005), Self-Starter (0.004), Database Administration (0.004), Pivot Tables (0.004), Market Analysis (0.004), Technical Support (0.002), Microsoft Excel (0.002)	0.011
16	Delivery Driver And Technician	Rotech Healthcare	Physical Abilities (0.000), Lifting Ability (0.000), Caregiving (0.000), Patient Contact (0.000), Patient Transportation and Transfer (0.000), HAZMAT (0.000), Hazardous Materials Endorsement (0.000)	0
17	Vice President Underwriting	Morgan Stanley	Workflow Management (0.005), Written Communication (0.003), Detail-Oriented (0.002), Financial Analysis (0.001), Mortgage Underwriting (0.001), Staff Management (0.001)	0.002
18	Quality Assurance Engineer	Amazon	Computer Engineering (0.034), Software Development (0.027), User Interface (UI) Design (0.016), Software Quality Assurance (0.010), Black-box testing (0.009), Quality Assurance and Control (0.003), Consumer Electronics (0.002)	0.014
19	Sales Associate	GNC	Sales (0.001), Retail Industry Knowledge (0.000), Retail Sales (0.000), Basic Mathematics (0.000)	0
20	Dog And Cat Department Manager	Petco	Creativity (0.007), Leadership (0.003), Budgeting (0.001), Sales Goals (0.001), Retail Industry Knowledge (0.000), Physical Abilities (0.000), Inventory Management (0.000)	0.002

Table A3. Job Titles with the Highest Average AI-relatedness Measures

This table reports the job titles in Burning Glass with the highest average job-level AI measure ω_j^{AI}. We only include job titles that have at least 50 job postings and are matched to Compustat firms.

	Job Title	Avg. Continuous AI Measure
1	Artificial Intelligence Engineer	0.497
2	Senior Data Scientist - Machine Learning Engineer	0.394
3	Lead Machine Learning Scientist - Enterprise Products	0.369
4	AI Consultant	0.369
5	AI Senior Analyst	0.358
6	Machine Learning Engineer	0.315
7	Technician Architecture Delivery Senior Analyst AI	0.311
8	Artificial Intelligence Analyst	0.308
9	Software Engineer, Machine Learning	0.307
10	Artificial Intelligence Architect	0.303
11	Machine Learning Researcher	0.300
12	Computer Vision Engineer	0.293
13	Senior Machine Learning Engineer	0.286
14	Senior Machine Learning Scientist	0.281
15	Senior Software Engineer - Machine Learning	0.278
16	Senior Engineer II - Data Scientist	0.265
17	Senior Machine Learning Researcher	0.264
18	Artificial Intelligence Consultant	0.263
19	Computer Vision Scientist	0.256
20	Lead Machine Learning Researcher	0.255
21	Senior AI Engineer	0.248
22	Senior Applied Scientist	0.245
23	Senior Engineer - Machine Learning	0.243
24	Senior Risk Modeler	0.241
25	Data Scientist - Engineer	0.238
26	Artificial Intelligence Manager	0.237
27	Machine Learning Scientist	0.230
28	Applied Scientist	0.230
29	Software Engineer - Data Mining/Data Analysis/Machine Learning	0.229
30	Senior Associate, Data Scientist	0.223
31	Director, Data Scientist	0.222
32	Big Data Hadoop Consultant	0.214
33	Vice President- Data Analytics	0.211
34	Data Scientist Specialist	0.210
35	Applied Researcher	0.209
36	Data Scientist, Junior	0.205
37	Senior Staff Data Scientist	0.204
38	Principal Data Scientist	0.204
39	Director, Data Science	0.203
40	Research And Development Engineer - Data Mining/Data Analysis/Machine Learning	0.195
41	Manager, Data Scientist	0.192
42	Big Data Scientist	0.191
43	Architect - Relevance Infrastructure	0.191
44	Director Of Data Science	0.189
45	Senior Manager, Data Science	0.189
46	Data Science Specialist	0.188
47	Data Scientist II	0.188
48	Senior Data Science Engineer	0.187
49	Staff Data Scientist	0.186
50	Lead Data Scientist	0.186

Table A4. Firm-level Determinants of Job-postings-based AI Investments

This table reports the coefficients from regressions of cross-sectional changes in AI investments by U.S. public firms (in non-tech sectors) from 2010 to 2018 on the following ex-ante firm characteristics measured in 2010: log sales in column 1, cash/assets in column 2, R&D/sales in column 3, revenue TFP in column 4, log markup measured following De Loecker et al. (2020) in column 5, Tobin's Q in column 6, market leverage in column 7, return on assets (ROA) in column 8, and firm age in column 9. The dependent variable is the growth in the share of AI workers from 2010 to 2018 using the job postings data from Burning Glass. Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for industry sector fixed effects. The dependent variable is normalized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Share of AI Workers, 2010–2018									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Sales 2010	0.159***									0.224***
	(0.034)									(0.048)
Cash/Assets 2010		3.431***								1.414***
		(1.213)								(0.488)
R&D/Sales 2010			2.667**							2.806**
			(1.310)							(1.106)
Revenue TFP 2010				0.549						-0.542
				(0.965)						(0.334)
Log Markup 2010					0.400**					0.403*
					(0.194)					(0.222)
Tobin's Q 2010						0.172*				-0.002
						(0.097)				(0.091)
Market Leverage 2010							-0.921			-0.238
							(0.677)			(0.328)
ROA 2010								2.729**		2.462
								(1.334)		(1.565)
Firm Age 2010									-0.005	-0.003
									(0.004)	(0.002)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.186	0.264	0.165	0.145	0.163	0.243	0.159	0.171	0.149	0.405
Observations	1,192	1,192	1,192	1,120	1,192	1,013	1,139	1,188	1,192	959

Table A5. Summary Statistics

This table reports summary statistics for the sample of firms in our baseline regressions (including 1052 firms in the regressions with the resume-based measure and 935 firms in the regressions with the job-postings-based measure). All changes in variables are computed over 2010–2018. Changes in the numbers of trademarks and patents are measured as changes in log(1+number) to take into account firms with zero trademarks or patents. We follow the methodology proposed by Ganglmair et al. (2021) to distinguish between product patents and process patents. The number of product and process patents are de-trended using the entire patent sample due to the truncation of the patent sample in recent years. The change in the product mix is measured as the sum of annual changes from 2010 to 2018, where each annual change is the angle between the two word vectors indicating firms' product offerings in that year and the previous year following Hoberg et al. (2014). Log markup is measured as the log of the ratio of sales to cost of goods sold, following De Loecker et al. (2020). For each variable, we report the number of observations, the mean, the standard deviation, the median, and 1st, 5th, 10th, 25th, 75th, 90th, 95th, and 99th percentiles.

Variable Name	**N**	**Mean**	**Std. Deviation**	**p1**	**p5**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**	**p99**
Change in share of AI workers (Cognism)	1052	.0010	.0022	-.0018	-.00011	0	0	.00024	.0011	.0029	.0046	.014
Change in share of AI workers (Burning Glass)	935	.0046	.012	-.0033	0	0	0	0	.0034	.013	.026	.076
Change in log sales	1052	.45	.66	-1.2	-.61	-.24	.073	.39	.77	1.3	1.7	2.6
Change in log employment	1052	.3	.64	-1.8	-.67	-.35	-.036	.26	.61	1.0	1.4	2.2
Change in log market value	1010	.52	.72	-1.2	-.78	-.38	.1	.51	.94	1.4	1.7	2.6
Change in log number of trademarks	553	-.13	1.2	-3.0	-2.3	-1.8	-.92	0	.41	1.4	2.0	3.2
Change in log number of product patents	621	-.20	1.1	-2.9	-2.2	-1.8	-.94	.062	.85	.85	.85	1.5
Change in log number of process patents	621	-.067	.99	-3.0	-2.0	-1.5	-.63	.067	.76	.76	.76	1.5
Change in product mix	958	4.3	1.3	2.1	2.6	3.0	3.4	4.1	5.0	6.0	6.9	7.9
Change in log sales per worker	1052	.14	.39	-1.0	-.44	-.24	-.038	.12	.30	.56	.79	1.6
Change in revenue TFP	977	.0065	.36	-1.2	-.51	-.36	-.17	.0016	.17	.38	.55	1.2
Change in log COGS	1052	.38	.67	-1.6	-.80	-.34	.038	.35	.72	1.2	1.6	2.3
Change in log operating expense	1052	.42	.61	-1.3	-.57	-.22	.073	.37	.74	1.2	1.6	2.1
Employment in 2010 (thousands)	1052	23	55	.066	.21	.39	1.2	4.5	16	57	109	294
Sales in 2010 (millions)	1052	9104	24318	16	69	146	491	1601	5965	20732	50272	125805
Cash / Assets in 2010	1052	.16	.17	.00054	.0062	.014	.041	.11	.23	.41	.55	.70
R&D / Sales in 2010	1052	.055	.17	0	0	0	0	0	.029	.14	.23	1.1
Log markup in 2010	1052	.56	.47	-.34	.082	.14	.25	.44	.74	1.2	1.5	2.3

Table A6. AI Investments and Firm Growth across Non-Tech Sectors Using the Resume-based AI Measure

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous changes in AI investments among U.S. public firms (in non-tech sectors), separately by broad industry sector. Columns 1 and 2 consider firms in the manufacturing sector (2-digit NAICS = 31, 32, 33), columns 3 and 4 consider firms in the wholesale and retail trade sectors (2-digit NAICS = 42, 44, 45), columns 5 and 6 look at firms in the finance sector (2-digit NAICS = 52), and columns 7 and 8 include firms in the other non-tech sectors (all 2-digit NAICS sectors, except those listed above and 51 and 54). The changes in the share of AI workers are based on the resume data and standardized to mean zero and standard deviation of one within each sample. We consider two measures of firm growth: changes in log sales in odd columns and changes in log employment in even columns. Regressions are weighted by the number of Cognism resumes in 2010. All regressions include industry sector fixed effects and the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Manufacturing		Wholesale & Retail		Finance		Other	
	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.135**	0.125*	0.321***	0.357***	0.239**	0.264**	0.177***	0.125*
	(0.057)	(0.072)	(0.061)	(0.061)	(0.107)	(0.103)	(0.061)	(0.067)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.321	0.281	0.817	0.857	0.473	0.478	0.473	0.363
Observations	516	516	109	109	149	149	278	278

Table A7. AI Investments and Firm Growth in Tech Sectors Using the Resume-based AI Measure

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous changes in AI investments among U.S. public firms in tech sectors. Columns 1 and 2 consider firms in the information sector (2-digit NAICS = 51), and columns 3 and 4 consider firms in the professional and business services sector (2-digit NAICS = 54). The changes in the share of AI workers are based on the resume data and standardized to mean zero and standard deviation of one within each sample. We consider two measures of firm growth: changes in log sales in odd columns and changes in log employment in even columns. Regressions are weighted by the number of Cognism resumes in 2010. All regressions include industry sector fixed effects and the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Information		Prof. & Business Svcs	
	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.495***	0.409***	0.035	0.140*
	(0.125)	(0.114)	(0.125)	(0.073)
Industry FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Adj R-Squared	0.673	0.622	0.501	0.388
Obs	129	129	54	54

Table A8. AI Investments and Firm Growth: Long-differences Estimates Using the Job-postings-based AI Measure

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). We consider three measures of firm growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). The dependent variables are measured as growth from 2010 to 2018. The main independent variable is the growth in the share of AI job postings from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of job postings), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.150***	0.160***	0.161**	0.167**	0.146*	0.189***
	(0.055)	(0.045)	(0.076)	(0.050)	(0.083)	(0.068)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.273	0.452	0.320	0.526	0.338	0.461
Observations	935	935	935	935	903	903

Table A9. AI Investments and Firm Growth: Long-differences Estimates Using the Continuous Job-postings-based AI Measure

This table reports the coefficients from long-differences regressions of growth of U.S. public firms (in non-tech sectors) from 2010 to 2018 on the contemporaneous changes in the average job-level continuous AI measure across all Burning Glass job postings of each firm. The independent variable is the change in the firm-level average continuous AI-relatedness measures from 2010 to 2018, standradized to mean zero and standard deviation of one. Panel 1 presents results from the continuous measure based on all skills (ω_j^{AI}), and Panel 2 shows results from the continuous measure based on narrow AI skills ($\omega_j^{NarrowAI}$). The continuous measure based on narrow AI skills removes the impact of general programming or statistics skills not specific to AI (e.g., Python or linear regression). See Section 3.1 for detailed descriptions of these measures. We consider three measures of firm growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, log number of job postings), log industry wage, as well as characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5–digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel 1: Continuous All-skill AI Measure

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.143**	0.177***	0.144	0.130*	0.132	0.197**
	(0.069)	(0.053)	(0.093)	(0.069)	(0.095)	(0.076)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.254	0.432	0.306	0.521	0.324	0.446
Observations	935	935	935	935	903	903

Panel 2: Continuous Narrow AI measure

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.147***	0.174***	0.154*	0.133***	0.139	0.202***
	(0.057)	(0.041)	(0.079)	(0.050)	(0.086)	(0.067)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.271	0.443	0.317	0.525	0.335	0.459
Observations	935	935	935	935	903	903

Table A10. AI Investments and Firm Growth: Long-differences Estimates Using Alternative Cutoffs of the Job-postings-based AI Measure

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous changes in the share of AI job postings of U.S. public firms (in non-tech sectors). AI job postings are defined as job postings with continuous job-level measure ω_j^{AI} above 0.05 in Panel 1, and job postings with continuous job-level measure ω_j^{AI} above 0.15 in Panel 2. See Section 3.1 for the detailed description of the methodology. The independent variable is standardized to mean zero and standard deviation of one. We consider three measures of firm growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). Regressions are weighted by the number of Burning Glass job postings in 2010. All regressions control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number job postings), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel 1: Cutoff = 0.05

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.142**	0.168***	0.153*	0.138***	0.132	0.192***
	(0.058)	(0.042)	(0.080)	(0.049)	(0.087)	(0.067)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.268	0.454	0.317	0.528	0.332	0.460
Observations	935	935	935	935	903	903

Panel 2: Cutoff = 0.15

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.146**	0.140**	0.154*	0.106*	0.149	0.176**
	(0.065)	(0.056)	(0.085)	(0.058)	(0.092)	(0.082)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.261	0.437	0.311	0.520	0.334	0.453
Observations	935	935	935	935	903	903

Table A11. AI Investments and Firm Growth for Top AI-investing Firms in the Distribution of Resume-based AI Investments

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on measures of contemporaneous AI investments among U.S. public firms (in non-tech sectors). We consider three measures of firm growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). The independent variable is a dummy variable for firms having changes in the (resume-based) share of AI workers in the top 25% of the distribution (in Panel 1) or in the top 10% of the distribution (in Panel 2). Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel 1: Top 25% of AI-investing Firms

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Top 25% in AI Investment	0.297**	0.313***	0.351**	0.328***	0.251	0.197**
	(0.136)	(0.081)	(0.176)	(0.107)	(0.163)	(0.100)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.154	0.387	0.163	0.379	0.138	0.309
Observations	1,051	1,051	1,051	1,051	1,009	1,009

Panel 2: Top 10% of AI-investing Firms

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Top 10% in AI Investment	0.493***	0.491***	0.648***	0.579***	0.546***	0.518***
	(0.158)	(0.078)	(0.186)	(0.115)	(0.205)	(0.113)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.197	0.413	0.230	0.415	0.191	0.346
Observations	1,051	1,051	1,051	1,051	1,009	1,009

Table A12. AI Investments (Including External AI Software) and Firm Growth Using the Resume-based AI Measure

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The main independent variable is the growth in the share of AI-utilizing workers (including both workers with AI skills and workers with jobs referencing external AI software, such as IBM Watson) from 2010 to 2018, standardized to mean zero and standard deviation of one. We consider three measures of firm growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.242***	0.228***	0.289***	0.265***	0.285***	0.279***
	(0.056)	(0.050)	(0.081)	(0.062)	(0.075)	(0.063)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.245	0.445	0.268	0.448	0.253	0.397
Observations	1,023	1,023	1,023	1,023	994	994

Table A13. AI Investments and Firm Growth : Controlling for Other Technologies

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous changes in AI investments among U.S. public firms (in non-tech sectors), controlling for investments in other (non-AI-specific) technologies. Columns 1 and 2 control for the 2010-2018 change in the firm's share of non-AI IT jobs, columns 3 and 4 control for the change in the share of robot-related jobs, columns 5 and 6 control for the change in the share of non-AI data-related jobs, and columns 7 and 8 control for the changs in the share of non-AI data analysis jobs. An IT job is defined as a job for which at least 10% of the required skills are in the "Information Technology" skill cluster; a robot-related job is a job with a robot relatedness score (constructed with the same methodology as the AI-relatedness score but using the core skill of "Robotics") above 0.1; a data-related job is a job with at least 10% of required skills in data-related skill clusters; a data analysis job is a job with at least 10% of required skills in the "Analysis" skill cluster. All measures are standardized to mean zero and standard deviation of one. Panel 1 considers the resume-based measure of the share of AI workers, while Panel 2 looks at the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. All regressions control for industry sector fixed effects and the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of jobs—resumes in Panel 1 and job postings in Panel 2), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel 1: AI measure from resume data

	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.207***	0.217***	0.208***	0.219**	0.192***	0.203***	0.195***	0.207***
	(0.053)	(0.075)	(0.063)	(0.084)	(0.049)	(0.070)	(0.053)	(0.074)
Δ Share Non-AI IT Workers	0.138***	0.114**						
	(0.051)	(0.045)						
Δ Share Robot Workers			-0.016	-0.016				
			(0.032)	(0.040)				
Δ Share Non-AI Data Workers					0.136***	0.131***		
					(0.037)	(0.034)		
Δ Share Non-AI Data Analysis Workers							0.073**	0.068**
							(0.030)	(0.031)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.456	0.430	0.434	0.419	0.465	0.441	0.443	0.425
Observations	970	970	970	970	970	970	970	970

Panel 2: AI measure from job postings data

	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment	Δ Log Sales	Δ Log Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.158***	0.119**	0.154***	0.128***	0.160***	0.120***	0.165***	0.128***
	(0.039)	(0.047)	(0.038)	(0.047)	(0.039)	(0.045)	(0.040)	(0.047)
Δ Share Non-AI IT Workers	0.138***	0.178***						
	(0.052)	(0.057)						
Δ Share Robot Workers			0.071	0.015				
			(0.048)	(0.049)				
Δ Share Non-AI Data Workers					0.054	0.093		
					(0.064)	(0.072)		
Δ Share Non-AI Data Analysis Workers							0.019	0.022
							(0.050)	(0.052)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.459	0.540	0.445	0.525	0.443	0.528	0.441	0.525
Observations	935	935	935	935	935	935	935	935

Table A14. Resume-based AI Investments and Firm Growth: Controlling for Detailed Industry Fixed Effects

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors), with detailed industry fixed effects. We consider three measures of growth: changes in log sales (columns 1–4), changes in log employment (columns 5–8), and changes in log market value (columns 9–12). The main independent variable is the growth in the share of AI workers (based on the resume data) from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Columns 1, 5, and 9 include the baseline specification with the industry sector fixed effects; columns 2, 6, and 10 control for 3-digit NAICS fixed effects; columns 3, 7, and 11 control for 4-digit NAICS fixed effects; columns 4, 8, and 12 control for 5-digit NAICS fixed effects. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales				Δ Log Employment				Δ Log Market Value			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	0.203***	0.186***	0.198**	0.212**	0.217***	0.189**	0.197*	0.202*	0.224***	0.182**	0.198**	0.215**
	(0.061)	(0.065)	(0.089)	(0.088)	(0.078)	(0.083)	(0.107)	(0.104)	(0.078)	(0.079)	(0.099)	(0.097)
NAICS2 FE	Y	N	N	N	Y	N	N	N	Y	N	N	N
NAICS3 FE	N	Y	N	N	N	Y	N	N	N	Y	N	N
NAICS4 FE	N	N	Y	N	N	N	Y	N	N	N	Y	N
NAICS5 FE	N	N	N	Y	N	N	N	Y	N	N	N	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.428	0.495	0.516	0.526	0.417	0.478	0.555	0.566	0.364	0.496	0.569	0.600
Observations	1,051	1,046	1,010	940	1,051	1,046	1,010	940	1,009	1,005	967	894

Table A15. Resume-based AI Investments and Firm Growth: Controlling for Industry- and Firm-level Pre-trends

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). In this table, we control for past industry and firm growth, which helps address the concern that AI-investing firms might already be on higher growth trajectories prior to AI investments. We consider three measures of firm growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). The main independent variable is the growth in the share of AI workers (based on the resume data) from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects and include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Additionally, columns 1, 3, and 5 control for industry-level growth in sales and employment from 2000 to 2008 (at the 5-digit NAICS level), and columns 2, 4, and 6 control for firm-level growth in sales and employment from 2000 to 2008. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.196***	0.181***	0.210***	0.203***	0.212***	0.188***
	(0.057)	(0.047)	(0.075)	(0.066)	(0.070)	(0.060)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Industry pre-trend	Y	N	Y	N	Y	N
Firm pre-trend	N	Y	N	Y	N	Y
Observations	1,003	814	1,003	814	961	788

Table A16. Resume-based AI Investments and Firm Growth: Controlling for State FE and Tobin's q

This table reports the coefficients from long-differences regressions of firm growth from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors), with additional controls for state FE and Tobin's q. We consider three measures of growth: changes in log sales (columns 1 and 2), changes in log employment (columns 3 and 4), and changes in log market value (columns 5 and 6). The main independent variable is the growth in the share of AI workers (based on the resume data) from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects, state fixed effects, and the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number ofresumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Columns 2, 4, and 6 also control for Tobin's Q in 2010, defined as market value of assets divided by book value of assets. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales		Δ Log Employment		Δ Log Market Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.177***	0.156***	0.180***	0.158***	0.194***	0.170***
	(0.060)	(0.044)	(0.069)	(0.053)	(0.070)	(0.053)
Tobin's Q 2010		0.225***		0.233***		0.245***
		(0.065)		(0.063)		(0.076)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
NAICS3 FE	N	N	N	N	N	N
Adj R-Squared	0.493	0.554	0.510	0.564	0.425	0.474
Observations	1,045	1,003	1,045	1,003	1,000	999

Table A17. Past Resume-based AI Investments and Future Firm Growth

This table reports the coefficients from a predictive regression of firm growth during the later part of our sample (2015–2020) on growth in AI investments during the earlier part of the sample (2010–2015) among U.S. public firms (in non-tech sectors). The dependent variables are changes in log sales in columns 1 and 2, and changes in log employment in columns 3 and 4. The main independent variable is the growth in the share of AI workers (based on the resume data) from 2010 to 2015, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales		Δ Log Employment	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.128**	0.084**	0.149*	0.088*
	(0.053)	(0.041)	(0.079)	(0.052)
Industry FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.250	0.372	0.211	0.357
Observations	990	990	982	982

Table A18. AI Investments and Product Innovation Using the Job-postings-based AI Measure

This table reports the coefficients from long-differences regressions of the changes in measures of product innovation from 2010 to 2018 on the contemporaneous changes in AI investments by U.S. public firms (in non-tech sectors). The dependent variables are the change in log(1+number of trademarks) in columns 1 and 2; the change in log(1+number of product patents) in columns 3 and 4; and the change in the product mix in columns 5 and 6. Product patents are patents with over 50% of the claims being product claims, following the categorization in Ganglmair et al. (2021). The change in the product mix is measured as the sum of annual changes from 2010 to 2018, where each annual change is the angle between the two word vectors indicating firms' product offerings in that year and the previous year (the word vectors are constructed as in Hoberg et al. (2014). The main independent variable is the job-postings-based measure of the growth in the share of AI workers from 2010 to 2018, which is standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of job postings), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Number of Trademarks		Δ Log Number of Product Patents		Change in Product Mix	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.132**	0.059	0.169***	0.198***	0.109***	0.076**
	(0.057)	(0.063)	(0.029)	(0.050)	(0.033)	(0.036)
Industry FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Observations	505	505	560	560	860	860

Table A19. AI Investments and Product Innovation: IV Estimates Using the Resume-based AI Measure

This table estimates the relationship between AI investments and product innovation from 2010 to 2018 for U.S. public firms (in non-tech sectors), where firms' AI investments are instrumented with ex-ante firm-level exposure to AI-skilled graduates from AI-strong universities (see the definition of the instrument in Section 4.3 and the details of instrument construction in Appendix A). The independent variable is the change in the share of AI workers from 2010 to 2018 based on the resume data. The independent variable and the instrument are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. We consider the change in log(1+number of trademarks) in columns 1 to 4, the change in log(1+number of product patents) in columns 5 to 8, and the change in the product mix in columns 9 to 12. Product patents are patents with over 50% of the claims being product claims, following the categorization in Ganglmair et al. (2021). The change in the product mix is measured as the sum of annual changes between from 2010 to 2018, where each annual change is the angle between the two word vectors indicating firms' product offerings in that year and the previous year, following Hoberg et al. (2014). All specifications control for industry sector fixed effects and ex-ante exposure to universities that are strong in computer science research as well as top 10 universities. Columns 2–4, 6–8, and 10–12 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Columns 3, 4, 7, 8, 11, and 12 additionally control for firm-level changes in log sales and log employment from 2000 to 2008. Columns 4, 8, and 12 add state fixed effects. Standard errors are clustered at the 5-digit NAICS industry level, and reported in parentheses. The first-stage F-statistics of the instrument are reported for all specifications. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Number of Trademarks				Δ Log Number of Product Patents				Change in Product Mix			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	0.217	0.498	0.670**	0.700**	0.240	0.277	0.480***	0.431**	0.176	0.233	0.227	0.476**
	(0.215)	(0.366)	(0.316)	(0.278)	(0.164)	(0.187)	(0.178)	(0.216)	(0.282)	(0.260)	(0.238)	(0.236)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
CS Control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Baseline Controls	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Control Pre-trend	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
State FE	N	N	N	Y	N	N	N	Y	N	N	N	Y
F Statistic	12.1	12.3	9.9	18.8	11.6	20.6	30.6	32.0	13.2	13.2	10.2	15.0
Observations	528	528	435	426	586	586	479	469	932	932	725	717

Table A20. AI Investments and Operating Costs Using the Job-postings-based AI Measure

This table reports the coefficients from long-differences regressions of changes in firm operating costs and firm productivity from 2010 to 2018 on contemporaneous changes in AI investments by U.S. public firms (in non-tech sectors). The main independent variable is the change in the share of AI workers (based on the job postings data) from 2010 to 2018, standardized to mean zero and standard deviation of one. We look at two measures of operating costs: log COGS in columns 1 and 2 and log operating expenses in columns 3 and 4. We consider two measures of productivity: log sales per worker (columns 5–6) and revenue TFP (columns 7–8). Revenue TFP is the residual from regressing log revenue on log employment and log capital (constructed using the perpetual inventory method), with separate regressions for each industry sector. In columns 9 and 10, the dependent variable is the change in log(1+number of process patents), where process patents are patents with over 50% of the claims being process claims, following the categorization in Ganglmair et al. (2021). Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, and 8 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of job postings), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log COGS		Δ Log Operating Expense		Δ Log Sales per Worker		Δ Revenue TFP		Δ Log Number of Process Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.153***	0.143***	0.148***	0.151***	-0.011	-0.007	-0.018	-0.012	0.031	0.064
	(0.039)	(0.035)	(0.051)	(0.040)	(0.050)	(0.031)	(0.042)	(0.031)	(0.048)	(0.064)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.246	0.390	0.251	0.410	0.375	0.555	0.287	0.422	0.732	0.760
Observations	935	935	935	935	935	935	874	874	560	560

Table A21. Resume-based AI Investments and Productivity of Early Adopters

This table reports the coefficients from long-differences regressions of changes in firm productivity from 2010 to 2018 on changes in AI investments by U.S. public firms (in non-tech sectors) from 2010 to 2014. We consider two measures of productivity: log sales per worker in columns 1 and 2 and revenue TFP in columns 3 and 4. Revenue TFP is the residual from regressing log revenue on log employment and log capital (constructed using the perpetual inventory method), with separate regressions for each industry sector. The main independent variable is growth in the share of AI workers based on the resume data from 2010 to 2014. All independent variables are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also include the baseline controls all measured as of 2010: firm-level characteristics (log sales, cash/assets, R&D/sales, log markup, and log number of resumes), log industry wage, and characteristics of the commuting zones where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers). Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Log Sales per Worker		Δ Revenue TFP	
	(1)	(2)	(3)	(4)
Δ Share AI Workers 2010-2014	-0.075	-0.042	-0.041	-0.016
	(0.065)	(0.042)	(0.053)	(0.039)
Industry FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.225	0.387	0.210	0.348
Observations	1,032	1,032	960	960

Table A22. Resume-based AI Investments and Industry Growth within a Balanced Panel of Firms

This table reports the coefficients from industry-level long-differences regressions of the changes in total industry sales and employment on contemporaneous changes in AI investments for a balanced panel of firms existing in both 2010 and 2018. Each observation is a 5-digit NAICS industry, and we exclude tech sectors. The independent variable is the change in the share of AI workers based on the resume data from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the total (industry-level) number of Cognism resumes in 2010. The dependent variables are the changes, from 2010 to 2018, in log total sales (not including entrants and exits between 2010 and 2018) in columns 1 and 2 and in log total employment in columns 3 and 4. All measures are calculated using Compustat firms that exist at the beginning (2010) and the end (2018) of our sample. All specifications control for industry sector fixed effects. Regressions in columns 2 and 4 also include industry-level controls for log total employment, log total sales, and log average wage in 2010. Standard errors are robust against heteroskedasticity and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Sales		Employment	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.172***	0.188***	0.195***	0.211***
	(0.058)	(0.045)	(0.074)	(0.062)
Industry FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	275	275	275	275

Table A23. AI Investments and Changes in Industry Growth and Concentration Using the Job-postings-based AI Measure

This table reports the coefficients from industry-level long-differences regressions of the changes in industry sales, employment, and concentration on contemporaneous changes in industry-level AI investments. All industry-level variables are calculated for all firms in Compustat (regardless of whether they are in our main regression sample in Table 3 or not). Each observation is a 5-digit NAICS industry, and (as in our main analysis) we exclude tech sectors. The independent variable is the change in the share of AI workers (based on the job postings data) from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the total (industry-level) number of Burning Glass job postings in 2010. The dependent variables are the changes, from 2010 to 2018, in log total sales in columns 1 and 2, log total employment in columns 3 and 4, the Herfindahl-Hirschman Index (HHI) in columns 5 and 6, and the market share of the top firm in an industry in columns 7 and 8. All specifications control for industry sector fixed effects. Regressions in columns 2, 4, 6, and 8 also include industry-level controls for log total employment, log total sales, and log average wage in 2010. Standard errors are robust against heteroskedasticity and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log Sales		Log Employment		HHI		Top Firm Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.192***	0.194***	0.187*	0.171*	0.040***	0.047***	0.028***	0.035***
	(0.046)	(0.048)	(0.099)	(0.096)	(0.007)	(0.007)	(0.007)	(0.008)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Observations	261	261	261	261	254	254	254	254